Timetables, Attendance and Academic Achievement in Higher Education

Accepted for publication in the European Economic Review

https://doi.org/10.1016/j.euroecorev.2026.105457

Timetables, Attendance and Academic Achievement in Higher Education *

Adeline Delavande

University of Technology Sydney; Nova School of Business and Economics

Emilia Del Bono, **Angus Holford**†

Institute for Social and Economic Research, University of Essex

Kevin Williams

Occidental College

Accepted in *European Economic Review*

Journal version at

DOI: https://doi.org/10.1016/j.euroecorev.2026.105457

August 20, 2026

Abstract

Managing time is an important aspect of student success. In this paper, we identify the impacts of a student's timetable on their attendance, study habits, and academic achievement. We use detailed administrative and survey data from a public UK university that includes students from a broad range of degree programmes. Our data feature quasi-random assignment of students to their timetables and measure their individual hourly attendance decisions. We consider multiple aspects of timetables including single-class days, back-to-back classes, time-of-day, day-of-instruction and total hours. We find that student attendance is highly dependent on timetable structure. Single-class days reduce attendance and back-to-back classes raise it. Attendance also varies by time-of-day and day-of-week. We document that students compensate for marginal non-attendance at some events with increased attendance at others within the same module and that more conscientious students respond by increasing study time. Net of all behavioural responses, however, these timetable features and attendance choices do not have systematic impacts on academic achievement. Subsample analysis suggests that lab-based modules and compulsory modules are where timetables may play the most meaningful role in impacting marks.

Keywords: Human capital, Higher Education, Timetables, Schedules, Education production, Attendance, Effort

*Delavande, Del Bono and Holford's work on this paper is funded by the Economic and Social Research Council (ESRC) through the open call grant 'Inequality in Higher Education Outcomes in the UK: Subjective Expectations, Preferences and Access to Information' [ES/M008622/1], and the Research Centre on Micro-Social Change (MiSoC) [ES/S012486/1]. For the purpose of Open Access, the authors have applied a CC BY public copyright license to any Author Accepted Manuscript (AAM) version arising from this submission. Fieldwork costs were met through the open call grant, and Williams received travel and subsistence support from MiSoC in order to collaborate on this paper. Delavande also acknowledges funding by European Commission (Project no. 101086974). Delavande, Del Bono and Holford gratefully acknowledge the help of Richard Martin at the University of Essex for providing the administrative data used in this paper. Thanks to the anonymous referees for their feedback and substantial improvement to the paper during the editorial process.

†Corresponding author: E-mail: ajholf@essex.ac.uk

1 Introduction and background

The move from secondary to higher education presents students with a number of new challenges. Among them is adjusting to new daily timetables that typically feature fewer in-class hours and less oversight. A weekday with no obligations can seem too good to be true. Identifying the factors that support or hinder students in staying on track is critical for improving academic outcomes. As work-from-home and hybrid-work has become standard for many college graduates (Bloom *et al.*, 2024), the structure of a university timetable has come to more closely match the professional one. In this paper, we examine how the sequencing, timing, spacing, and distribution of student's timetables affects class attendance and academic performance at university.

We study this question using rich administrative and survey data from a large UK public university. The BOOST2018 study (Delavande *et al.*, 2022) tracks an entire cohort of undergraduate students and includes over 300,000 individual student attendance decisions, linked to academic outcomes across a wide range of programmes. For a subset of students, we additionally observe detailed survey data on study time, study habits, and personality traits, enabling us to explore mechanisms and heterogeneity. This is a representative higher education setting where students have significant autonomy in organizing their time. While this autonomy can help optimize time allocation, as has been seen in the labour market (Beckmann *et al.*, 2017; Boltz *et al.*, 2023), it may also lead to procrastination and present bias, hindering academic success.

Our identification strategy exploits quasi-random variation in students' timetables during their first year at university. Students within the same programme (i.e. major) enroll in multiple compulsory modules. Each module includes a large-group lecture - scheduled at the same time for all students - and a smaller teaching event(s) (e.g., lab, tutorial, seminar) for which students are randomly assigned to different time slots in smaller groups. This random allocation generates exogenous variation in daily start times, event spacing, and total daily event loads. We use this variation to estimate the causal effects of timetable structure on both attendance and academic performance.

Our first key finding is that students' daily attendance decisions are meaningfully influenced by their timetable structure. Students are significantly more likely to attend classes when events are scheduled back-to-back, with attendance increasing by 1.5 percentage points relative to a mean attendance rate of 65%. In contrast, isolated events, those occurring alone on a given day, reduce attendance by 0.9 percentage points. While students are less likely to attend isolated events, they appear to compensate by attending other sessions for the same module at above-average rates, leading to higher overall attendance at the module level. We interpret this as evidence of consistent strategic time management: students make deliberate trade-offs in their attendance decisions based on convenience and opportunity cost. We also find that events held in the afternoon or on Mondays are associated with higher attendance rates.

Our second key finding concerns the link between timetables and achievement. Across our entire population, timetable structure does not have a systematic effect on academic achievement, despite its effect on attendance. There are different explanations for why we do not find impacts on achievement. One is that students adjust their behaviour in response to less-than-optimal schedules. In particular, the autonomy in time management afforded by our multi-module, optional attendance setting, could be playing a protective role by enabling students to compensate for marginal non-attendance by reallocating effort toward other productive activities within and across modules. Equally, this finding is consistent with low productivity for marginal attended events, for example due to fatigue, low class engagement, or depreciation of learning between teaching and assessment.

To shed light on the mechanisms at play we consider heterogeneity by student- and module-type, and further use linked survey data on time use, study behaviour, and non-cognitive traits. These analyses provide some evidence that timetables may matter for marks in particular settings. Lab-based modules, which are concentrated in STEM subjects, show a closer link between attendance and marks, while in compulsory modules, which are higher-stakes for students, heavier daily course loads lead to lower marks.

Our rich administrative and survey data allow us to examine other potential mechanisms not typically observed. We find that average study hours are not systematically affected by timetable structure, but students do differ in their responses based on non-cognitive traits. In particular, more conscientious students, who may have a lower "cost of focused effort" (Lundberg, 2013), are better able to take advantage of scheduling features; such as back-to-back events that create longer uninterrupted blocks for study; by reallocating time toward more productive self-directed learning. In contrast, less conscientious students reduce study time in response to dispersed or isolated events. We also find that off-campus residents are more responsive to back-to-back scheduling, consistent with the presence of commuting costs.

Our paper contributes to multiple strands of literature within education and productivity. We build on findings from the time-of-day literature that finds early morning is detrimental to learning (Carrell *et al.*, 2011; Diette & Raghav, 2017; Edwards, 2012; Groen & Pabilonia, 2019; Heissel & Norris, 2017) and associates the afternoon with better performance than the morning (Cortes *et al.*, 2012; Cotti *et al.*, 2018; Dills & Hernandez-Julian, 2008; Haggag *et al.*, 2021; Lusher & Yasenov, 2018). We extend this literature by moving beyond analysis of time of day to study the causal impact of the *structure* of timetables; the order, spacing, and arrangement of classes; on attendance and performance. This dimension of scheduling remains largely understudied. Williams & Shapiro (2018) find that fatigue brought on by prior (especially back-to-back) classes earlier in the day offset the benefit of afternoon events. Their findings are similar to those in primary school settings (Pope, 2015; Rice *et al.*, 2002), which also feature mandatory attendance and low-autonomy. In contrast, we examine a generalizable higher education context where students have considerable autonomy and fewer in-person event hours than primary school, allowing us to capture behavioural responses to scheduling constraints more directly. Our setting is also closer to many professional settings, where workers need to manage their time and be productive without direct oversight (Bloom *et al.*, 2014). The quasi-experimental design afforded by our setting can therefore provide insights into use of autonomy in and away from these workplaces.

We also contribute to the literature on the relationship between attendance and academic achievement. Especially with recent decreases to in-person attendance due to Covid-induced changes in norms (Williams, 2022), understanding this relationship is timely. Class attendance is positively correlated with achievement, but not necessarily causally (Romer, 1993). Our paper distinguishes itself by both observing specific attendance choices made with autonomy and capturing a broad range of departments. Prior studies measuring detailed attendance focus on a single module or department (often economics) and find a positive association between attendance and achievement (Andrietti & Velasco, 2015; Chen & Lin, 2008; Cohn & Johnson, 2006; Cortinhas, 2025; Dobkin *et al.*, 2010). With similar assignment mechanisms, Arulampalam *et al.* (2012) use the time in the week that a class meets as an IV for attendance and find that attendance improves marks by 1.5 marks out of 100.

Meanwhile, studies that examine attendance on a university-wide scale have not found a strong causal link to achievement. Kapoor *et al.* (2021) exploits a university-wide attendance policy and finds no impact of attendance for a locally-treated group of students. Bratti & Staffolani (2013) finds that attendance only matters in mathematics-heavy courses. Our results show the strongest correlation between attendance and achievement in lab-based modules, but similar to the papers looking university-wide, we do not see strong evidence that marginal attendance choices impact marks.

The effect of attendance and timetables likely depends on the institutional context and the ability of students to exercise autonomy (Delavande *et al.*, 2021; Goulas *et al.*, 2023). Like Goulas *et al.* (2023), we also find that students take advantage of the autonomy offered by non-compulsory attendance to adjust the composition of their attendance and study; but unlike them, we find no evidence that timetable structures that provide more scope for this reallocation improve grades, even among highly conscientious students. When students have less autonomy and more fully-scheduled days, such as at military academies (Carrell *et al.*, 2011; Williams & Shapiro, 2018) or in secondary school (Pope, 2015; Rice *et al.*, 2002), timetables exhibit a greater impact on grades and marks because students have less capacity to adjust and a greater potential for fatigue.

Section 2 will describe our institutional setting. Section 3 summarizes our data and explains our measures of timetable structure. Section 4 describes our empirical model, identification, and provides balance checks. Results are discussed in Section 5. Section 6 concludes.

2 Institutional setting

Our setting is a large, public UK university. Between 2015/16 and 2023/24, it has been classified at different times as both a "Medium Tariff" (middle tercile) and a "Low Tariff" (bottom tercile) institution (Department for Education, 2024). This classification reflects the prior qualifications of UK-domiciled entrants. It places the university at approximately the 33rd percentile nationally in terms of incoming academic attainment. The intake is gender-balanced, and the share of students whose parents have a university degree is similar to the national average

(45.6% v. 42.4%). The university enrolls a somewhat higher proportion of Black British students (24.7% of UK-domiciled students versus 7.5% nationally), as well as EU (16.2% v. 5.7%) and rest-of-world International students (11.7% v. 9.1%) (Delavande *et al.*, 2025). The student body, therefore, resembles that of broad-access urban and metropolitan public universities in the US or Germany, but not elite private or flagship institutions. We expect our results to be informative for the broad middle of the higher education sector in countries with a comparable system.

The structure of the academic year, organization, and assessment of degree courses at this university is representative of most universities in England. Students apply and are accepted for a specific degree programme (i.e. major), which can be for one subject (e.g. Economics), or a combination (e.g. Politics, Philosophy and Economics). There is limited scope to switch programmes without re-starting studies, meaning students effectively make their programme choice before arriving at university.

Undergraduate degrees typically last three years. An illustrative timeline of an academic year is shown on the left-hand side of Figure 1. Within an academic year, teaching takes place during an Autumn term from October to December and a Spring term from January to March, both lasting 10 weeks and followed by a four week vacation. There is a shorter Summer term starting in late-April, lasting three weeks, in which revision lectures take place before an exam period in May and early June.

2.1 Module and timetable structure

Material is taught and assessed in *modules* (courses in the US). First year students must take modules worth 120 ‘Level 4’ credits in the UK Credit Accumulation and Transfer Scheme. These are typically arranged as 8 single-term 15-credit modules, 4 two-term 30-credit modules, or some combination of the two. Students from multiple degree programmes may be present within one module. For example, Politics, Philosophy and Economics programme students may be required to take the same introductory microeconomics module as those in the plain Economics programme.

Timetables repeat weekly during a term. Teaching takes place from 0900-1800 on Mondays, Tuesdays, Thursdays, and Fridays, and from 0900-1300 on Wednesdays.[1] A unique event is

[1]This is in common with most universities in the UK, to accommodate the majority of inter-university sports

identified by the date, time, and location of its occurrence.

Each week, most modules have a single *lecture*, where all enrolled students are taught at the same time by the same instructor. A module will also feature smaller practical or interactive sessions that, depending on the subject, are structured as a class, lab, seminar, or workshop. We collectively refer to these as *group events*. Students enrolled in a module are assigned into smaller groups to attend one or more group events together each week. These group events average 31 students and are potentially taught by different instructors within a module. The assignment of students into their smaller groups, taught at different times, provides our main source of identification, described in detail in section 3.3.

A student's weekly timetable is the set of all student-events on their timetable for a given week. Figure 2 shows two example weekly timetables for students enrolled in the same programme. Their lectures are all at common times, but they are assigned to some different group events, creating variation in their timetables.

2.2 Assignment to timetables

The university's overall timetable of teaching events is generated by a computer algorithm designed to fulfill a set of constraints submitted by the department administering each module. These specifications include a list of modules that are core or compulsory[2] for each relevant degree programme (whole-intake events for these therefore should not clash), the frequency and duration of each module's weekly events, the maximum number of students that may be accommodated, the equipment required, and the order or gaps of weekly events within each module (e.g. that group events should occur after the corresponding module's lecture). Allocation to group events is done randomly, subject to avoiding clashes with students' other teaching events. Students should not be taught for more than 5 consecutive hours.

It is important to note several features of this system and the context of higher education admissions and progression in England that support a causal interpretation of the effects of course timetables on attendance and performance.

First, students specialize early. The decision over institution and field of study must be

fixtures, under the aegis of British Universities and Colleges Sport (BUCS), that take place on Wednesday afternoons.

[2]Compulsory modules must be attempted, but the student can fail these and still proceed to the next year if their average across all modules exceeds 40%. Core modules must be passed in order to proceed to the next year.

made jointly, meaning students arrive at university to study an intended degree programme lasting a specified period of time. There is no process of major selection. Hence, the decision over university and programme of study will have been made before the timetable has been constructed or made available to students. Also, the vast majority of modules each student takes in the first year will be compulsory for their programme.[3]

Second, within a module, students cannot normally select their smaller groups based on their own preferences or expectations about productivity. Nor can any group event be filled by more proactive students registering for their preferred slot.

Third, in general, class instructors are unable to request a specific time of day to teach. The exception to this is staff employed on part-time contracts, in which case their designated working days and hours can be included in the constraints. This means that there is no reason why more senior or more effective teaching staff should be teaching at certain times or that staff characteristics should otherwise be correlated with student timetables. We do not have data on instructor assignment or characteristics, but we explore the potential for omitted variables bias driven by instructor quality in section 4.4.

The random assignment structure has two potential threats. First, the "exceptional circumstances" under which students can request a change in their group event assignment within a module include caring responsibilities, university sports fixtures, or (for those not living on campus only) excessive commutes. This introduces the possibility that some students' teaching group assignment is endogenous to their preferences, or to how costly the student finds it to request a change.

Second, while approximately 55% (178) of the degree programmes entail a complete slate of compulsory or core first-year modules, the other 45% (148) require students to select one or more 'optional' modules in order to complete the requisite number of credits for the year. These modules will contribute to the student's overall year mark, but are not required to be taken for the student's intended degree programme. 14% of first-year student-modules are optional, and 41% of students have at least one optional module. These optional modules potentially threaten identification in that they can be chosen by the student after the timetable is published. Some choices may not be feasible where teaching events clash with those for their compulsory

[3]It is possible to change degree programme and still complete on time, but only if pre-requisites for all the second and third-year modules in the alternative degree scheme have been studied before commencing them. More commonly, this entails repeating a year.

modules. Moreover, students choosing optional modules have no control over which teaching group they will be assigned to for group events, which provide our identifying variation.

The timing of information and key decisions is important in this context. The timetable is published to students at the end of August, approximately 2 weeks after A-Level (and equivalent-level qualification) results are released. The following few days are when students meeting the conditions of their offers will have their places confirmed, and students rejected by other universities may be granted admission at our institution through the centralised clearing system. Timetable publication is approximately 5 weeks before teaching starts, and during this window, students with insufficient scheduled credits from compulsory or core modules can choose their optional modules.

We present a comprehensive set of balancing checks in Section 4.4 that support the assignment of students to timetable characteristics as being quasi-random in practice. Specifically, we show that, conditional on the fixed effects we include in our models, timetable characteristics are orthogonal to both student and module characteristics.

2.3 Attendance policy

Across the university, attendance is strongly encouraged, but is not compulsory. Attendance at teaching events is recorded through an electronic swipe-card system. The university only intervenes, with an email enquiring whether the student requires any support, after 10 consecutive events of non-attendance, or if overall attendance falls below 50% across at least half a term. Escalations or sanctions beyond this are rare, being applied only in the case of extended non-engagement, including long-term low or non-attendance in combination with repeated non-completion of course requirements.[4] This means that students have considerable autonomy over their attendance decisions.

Figure 3 shows student attendance across the school year. The overall attendance rate is 65%, which is representative of large universities in the UK and abroad.[5] Attendance varies within and across terms. There is a steady decline in attendance over the course of both the spring and fall terms, consistent with Ha *et al.* (2024). We also see evidence that average

[4]These sanctions are potentially more serious for International students, for whom extended periods of non-engagement may be deemed non-compliant with their visa conditions.

[5]See Cortinhas (2025) and Montauban (2025), which see higher education attendance rates fall between 50-80% in European and American institutions.

attendance is higher in the fall than in the spring. The lower panel shows the likelihood that a student attends no events in a given week. This is below 5% throughout the fall, except for the final week. In the spring, complete absences are worse, starting off below 5%, but creeping up to between 5% and 10%, and close to 25% in the final week.

Overall, students have considerable autonomy over the allocation of their time in this university environment and this autonomy has been shown to increase productivity, especially for high-ability students (Bratti and Staffolini, 2013; Dolton et al., 2003; Goulas et al., 2023; Kapoor et al., 2021). Students who struggle with self-discipline or with understanding how to be productive on their own time may struggle with this autonomy (Fryer, 2011; Beattie et al., 2019). By contrasting timetable impacts on event-level with module-level attendance, on other study habits, and for higher-stakes modules, we shed light on how students exercise this autonomy.

2.4 Marks

Each student receives an overall mark for each module. This is a weighted average of a coursework mark and an exam mark. The coursework mark is awarded for an end-of-term test and/or a submitted piece of independently produced work completed during the term the module is taught or the vacation immediately afterwards. The exam mark is obtained during the summer exam period starting seven or 21 weeks after the end of the autumn and spring terms respectively.

All marks are awarded on a positive scale between 0 and 100. An overall mark of 40/100 is required to pass a module, with thresholds of 60 and 70 constituting Upper Second Class and First Class marks, respectively. Assessments are moderated by external examiners, with the intention that grading standards are comparable within subjects across universities (Naylor, Smith and Telhaj, 2016). Students must pass a sufficient number of first-year modules (Level 4 difficulty in the UK's National Qualifications Framework) to be allowed to progress into the second year. A final Degree Class is awarded based on a weighted average of second year (Level 5) and third year (Level 6) module overall marks and the number of modules meeting each class threshold.

We restrict our analysis to first-year marks. These are strongly predictive of students' final degree class. In our cohort, 64% of those receiving a First Class mark in their first year completed their programme on schedule *and* received a First Class Degree, compared with only 23% of those receiving an Upper Second Class mark in their first year, and 3% of those initially receiving a Lower Second. Final degree class plays a similar role to the GPA in the United States as a summary measure of performance in UK universities, being the main measure of academic performance seen by prospective employers, and there is a well established and significant degree class premium in graduate earnings (Feng & Graetz, 2017; Naylor *et al.*, 2016; Walker & Zhu, 2011). Moreover, higher performing first-year students are more likely to secure pre-graduation work experience or internships, which in turn may directly lead to job offers, since first-year marks will be the most recent information on academic attainment available to prospective employers (High Fliers Research, 2014; Mergoupis & Zubrickas, 2023).

3 Data

3.1 Data collection and sample selection

We study timetables using the BOOST2018 Study and focusing on the 2015-2016 academic year when study participants were in their first year of university. BOOST2018 is a longitudinal survey of undergraduate students enrolled in our university (Delavande et al., 2022). Figure 1 explains the timeline of the studies'recruitment and participation.[6]

During their first year, all students in our cohort were enrolled on courses at the same level of study within the UK's system of qualification credits, and of the same total credit value. Students are not yet retaking any modules that add to their timetable burden and the vast majority (86%) of student-modules are core or compulsory for the student's chosen degree programme.

We use administrative data on each student's timetable linked with records of their attendance obtained through the electronic swipe-card system, which is used for the administrative records of student engagement. The attendance data are very detailed, recorded at the

[6]Students were recruited into the study during their registration processes before the start of the first term in October 2015 and through the first half of the term. They were offered £5 as a thank-you for consenting to receive invitations to take online surveys through their university email addresses, and for the research team accessing and linking administrative records on their demographic and educational background, attendance, and academic performance held by the university. The surveys generally took about one hour. Participation was compensated by between £10 and £24.50 for online surveys and, on average, £30 for the laboratory sessions. The surveys were designed to collect information on students' academic investments (hours of study), non-academic investments (working for pay, participation in volunteering groups, etc), and a range of non-cognitive indicators.

level of student by module by week by event-type, enabling us in most cases to identify (non-)attendance for every student at every unique timetabled student-event (including the date, start-time, finish-time, and room), on every day of every week of the academic year.[7] This swipe-card system was put in place to record International students' compliance with their visa and immigration requirements. Some departments might monitor attendance much more closely than others and can make attendance at some classes effectively compulsory, but this is accounted for by our programme fixed-effects. These data are not subject to any of the recall or approximation biases inherent in self-reported data. They may have some measurement error, since students may either forget to swipe their card or give their card to a classmate to swipe on their behalf. We have no data on the extent of either problem, though we expect the former to quickly become a minimal concern as swiping in becomes part of the students' routine, while the latter requires a degree of effort to co-ordinate, making this unlikely to happen on a large scale. We will show that our results are stable when excluding International students and that the direction of our main findings would be robust even to quite extreme selective measurement error correlated with the class timetabling characteristics.

In our data, attendance is positively associated with marks. Figure 4 shows that students in the bottom decile of average attendance earn notably lower marks than those in the second decile and there are incremental increases thereafter. The correlation need not be causal, but it is clear why a university looking at similar raw data may want to encourage attendance. Most students have attendance rates between 50-85% and a decile change in attendance corresponds to roughly 6pp, or one additional event every other week.

3.2 Student characteristics

Table 1 summarizes student characteristics. Column 1 summarizes the whole cohort, and Column 2 summarizes students enrolled in BOOST2018, who form the primary sample for all estimates involving administrative data. These variables form the majority of our set of individual control covariates.[8]

Here British ("Home") students are classified by socioeconomic status (SES) according to

[7] In rare cases where students have two events on a module of the same narrow type (NB: seminars, labs, classes, tutorials are all different here) we only know how many of the events were attended. Where this corresponds to neither 100% nor 0% attendance, we impute attendance at specific events on a proportional basis.

[8] An exception is field of study, which is further disaggregated by fixed-effects for each degree programme and module being studied.

parental occupation.[9] Non-UK students are divided into those from the European Union, who at the time paid the same fees and had access to the same income-contingent loans for tuition and living costs as UK students, and non-EU 'International' students, who pay higher fees. Ethnicity is self-identified at the time of enrollment at the university, and parental experience of higher education at time of application. Students' entry tariff score is a measure of performance in qualifications from school or college. We divide these into quintiles within this institution's population (unequal numbers are due to ties). We also distinguish between those arriving with academic A-Level qualifications or other primarily vocational qualifications. The population and the enrolled sample are mostly well-balanced with a marginally higher proportion of Black students in the latter group. The enrolled sample is also more likely to have A-Level qualifications rather than missing or Level 3 qualifications, but this is not unusual in a longitudinal study (see e.g. Lynn & Borkowska, 2018; Department for Education, 2011).

These administrative data are supplemented by variables from the BOOST2018 waves 1-3 surveys that, by definition, are not recorded for BOOST2018 non-participants. In our balance checks for the validity of random assignment (section 4.4), we consider two non-cognitive traits we assume to be time-invariant, namely students' conscientiousness and experimentally-elicited discount factor (recorded for 1469 and 1202 students, 80% and 65% of the enrolled sample, respectively).

For the 2015/16 academic year, campus accommodation was limited. Students holding offers who wanted to live on campus could reserve accommodation and pay a deposit as early as the preceding January, and then confirmed their accommodation booking as soon as their enrollment was confirmed. We cannot rule out the possibility of endogenous sorting into campus accommodation based on *sight* of the timetable, but this would rely on initially campus-resident students to move out (either move to off-campus accommodation, or to dropout). Throughout the paper, we use the location of residence recorded at time of initial registration at the university, a week before teaching starts. This means our measure of campus residence is definitively predetermined with respect to *experience* of the timetable.

[9] "High SES" corresponds to a "Managerial or Professional" or "Intermediate" occupation in the UK National Statistics Socio-Economic Classification (categories 1-3). Where SES is missing, those living in neighbourhoods in the top 40% for young adults' higher education participation are classified as High SES, with a small proportion still unknown.

3.3 Timetable characteristics

We derive measures of what we describe as the *daily structure* of each student's timetable. These measures capture interdependence across events meeting on the same day and vary even among students sitting in the same group event of a module. We also consider event timing, including the *start-time* and *day-of-week* events takes place. For students enrolled in the same module, these measures will vary across, but not within, group events.

Our three primary daily structure characteristics are: *Only* events, *Back-to-Back* events, and *Cumulative Hours*. These are features of a student's timetable that may affect their attendance choices, alertness, and achievement. Each of these measures is generalizable to the timetable structure of any higher education setting.

Only is a dummy variable indicating that an event is the student's only one on that particular day. *Only* events are characterized by low expected cognitive fatigue for attendees, but also by a higher average cost of attendance (e.g., commuting for a single event).

Back-to-Back is a dummy for any events occurring in immediate succession with other(s) and with only a short break for the student to move between classrooms. We hypothesize that these events are efficient to attend, but may cause cognitive fatigue by expecting students to remain focused for long stretches of time (Ackerman & Kanfer, 2009; Jackson *et al.*, 2014). In Figure 2, we distinguish between *First of Back-to-Back*, a dummy that indicates the first event in a back-to-back sequence, and *Later in Back-to-Back* , which takes a value of 1 for all subsequent events in such a sequence. We do not disaggregate further because there is comparatively little additional variation to exploit.[10] Conditional on attending, *First of Back-to-Back* may be more productive for marks than *Later in Back-to-Back* events because the student will be less fatigued.

Cumulative Hours measures the total hours of event time a student has had up to that point of the day. The first event of a student's day always has a value of 0. Larger cumulative event loads have been associated with cognitive fatigue in Williams & Shapiro (2018) and Pope (2015). A default event, our omitted category where all three *daily structure* measures equal 0, would be one that is the first of the day on a student's schedule, but where they have at least one more event occurring later on that day, not immediately after the first. 23% of events in

[10] 84% of back-to-back sequences are two in a row before a break and 14% are three in a row. Sequences of four or more events in a row represent less than 2% of events in our data.

our main sample are default events.

Figure 2 conveys our variation and how measures of student's timetables are constructed. Both students attend the same Maths lecture at 1000 on Mondays, but due to the assignment of Student 1 and Student 2 to different group events for this module, it is an *Only* event for student 2, but not for Student 1. Their Maths group event is a *Back-to-Back* for Student 2 (at 1400 on Tuesday) but not Student 1 (at 1400 on Monday). The assignment to different Maths group events also affects the timetable characteristics of the Micro lecture they are both scheduled to attend at 1300 on Tuesday. The 0900 Wednesday Stats lecture is an example of a default event for both students.

Student timetables are summarized in Table 2. Our data set spans 170 modules, 11,346 events and 307,488 student-events. Columns 1 and 2 summarize student-events weighted equally (Column 1) and giving each student equal weight (Column 2). Column 3 reports totals of student-events aggregated into a representative week. The average student has 8.8 events per week on their timetable. Students attend 65% of events on average, or 5.8 events per week. Column 4 shows aggregates to the student-module level, which is the level at which marks are assessed. Students average 33 scheduled events per module, of which they attend 20. Column 5 summarizes data at the student-term level.

14% of all student-events are their *Only* event that day, an average of one per week. 21% of events are *First of Back-to-Back* events 27% are *Later in Back-to-Back*. The average student has 1.2 *Only* events per week, 4.4 per module, and 11.6 per term. Correspondingly, they have 1.8 back-to-back sequences per week, 6.9 per module and 17.3 per term. In subsequent module- and term-level analyses, our explanatory variables will be the share of that students' events that have each of these characteristics.

We also measure event timing. This includes the hour that instruction begins, which we capture with start-time dummies. Approximately 15% of events begin in each of the three morning hours (beginning 0900-1100), and roughly 10% of events begin in each hour from 1200 onward.[11] Not shown is a summary of class distribution across the week. Events occur with similar frequency on each day of the week, around 23% each, with the exception of Wednesdays (whose afternoons are reserved for extra-curricular activities), with only 9% of total events.

[11]Over 99% of observations begin at the start of an hour. We treat those starting at half-past the hour as *Later in Back-to-Back* if they follow an event finishing on the hour (which is, hence, treated as either *First of Back-to-Back* or *Later in Back-to-Back* as appropriate). However, we use the actual timetabled duration to construct *Cumulative Hours* for subsequent events.

Event timing variables vary across students enrolled in the same module but assigned to different group events.

The most common event types are lectures, accounting for 56% of all student-events, with students having around 5 lectures per week, 18 per module, and 47 per term. The average size for a lecture is 211 students. In all but six modules with lectures, the whole student intake meets together. This means that for most students in the same programme-module, lectures only exhibit variation in daily structure due to the arrangement of other events on each student's timetable. In a few modules with intakes above approximately 400, lectures are split into two similarly sized groups.

Classes and other types of small teaching group events (tutorials, seminars, workshops) make up 36% of observations. Labs, which are the most likely event type to be longer than an hour, account for an additional 8% of student-events. The average size for these group events is 31 students.

4 Empirical strategy

We focus on three primary outcomes: attendance, marks, and time use, each of which is measured at a different level of aggregation. This section describes the estimated equations for each outcome in order. Section 4.4 will empirically test the assumption of quasi-random assignment. Appropriate to the given outcome, we aggregate data at three different levels:

Student-event level: An individual lecture or group event for a student on a particular date. This is the level at which students make attendance decisions. See Column 2 of Table 2.

Student-module level: Aggregated averages of timetable characteristics for a student across all their student-events on a specific module. This is the level of variation for student marks. See Column 4 of Table 2.

Student-term level: Aggregated to averages of timetable characteristics for the student across all their student-events in a given term. This is the level of variation for surveyed outcomes (such as study time) that are not specific to a module.

4.1 Attendance

We investigate the impact of timetables on daily attendance at the student-event level by estimating Equation 1:

$$Att_{ipmt} = \beta_0 + \beta_1 Structure_{ipmt} + \lambda_p + \tau_m + \beta_2 \mathbf{X}_i + \beta_3 Mod_{mt} + \rho_t^w + \mu_t^h + \epsilon_{ipmt} \quad (1)$$

Here, Att_{ipmt} is an indicator of whether the student i in programme p attended the event for module m with timing t. Attendance varies at the student-event level and estimates can be interpreted as the marginal impacts on attendance. The vector $Structure_{ipmt}$ contains *Only*, *Back-to-Back*, and *Cumulative Hours*. β_1 contains the relationships between *daily structure* and student attendance. We scale all variables such that the coefficients can be interpreted as the percentage point impact on the probability of attendance at that event.

λ_p and τ_m represent programme and module fixed effects that control for student selection into programmes and average module difficulty. Timetables are random, conditional on λ_p and τ_m. $\mathbf{X}_i$ contains time-invariant individual controls shown in Table 3. Mod_{mt} contains module and teaching group controls. μ_h and ρ_w are time-of-day and day-of-week fixed effects, respectively. To aid parsimony while capturing key differences, we group start times and days as follows: For start-time, 0900 is the omitted category and other events are grouped as 1000-1200, 1300-1400, and 1500-1800. For day-of-week, Monday is the omitted category, other events grouped into 'midweek' (Tuesday-Thursday) and Friday. ϵ_{ipmt} is an error term, which, if identifying assumptions are met, will be conditionally uncorrelated with the vector $Structure_{ipmt}$. Standard errors are clustered at the individual level.[12]

We also investigate the impact of timetable characteristics on attendance at the student-module level, by estimating Equation 2:

$$\overline{Att}_{ipm} = \beta_0^m + \beta_1^m \overline{Structure}_{ipm} + \lambda_p^m + \tau_m^m + \beta_2^m \mathbf{X}_i + \overline{\rho}_{ipm}^{mw} + \overline{\mu}_{ipm}^{mh} + \epsilon_{ipm} \quad (2)$$

Here $\overline{Att}_{ipm}$ is the student's rate of attendance across all events in module m. The vector $\overline{Structure}_{ipm}$ contains the *share* of person i's events on module m that meet a criterion such as *Only*. $\overline{\rho}_{im}^{mw}$ and $\overline{\mu}_{im}^{mh}$ likewise capture the share of events for with a student-module that fall in

[12]We consider the robustness of our findings to allowing for teaching-group or module-level shocks creating correlation in residuals across students within a teaching group or module in Appendix Table A1.

each timing block.

β_1^m represents the impact of *all* events on a module having a trait such as *Only* versus none. Given the typical repeating weekly structure of one lecture and one group event per module, these coefficients could be divided by two to obtain the approximate impact of a change in the timetable characteristic of one of these events. This coefficient will also reflect any spillover effects of attendance decisions across events within a student's module.

4.2 Academic performance

Students' academic performance is measured by their marks, out of 100, for each module (Y_{ipm}). Marks vary at the student-module level:

$$Y_{ipm} = \theta_0^m + \theta_1^m \overline{Structure}_{ipm} + \lambda_p^m + \tau_m^m + \theta_2^m \mathbf{X}_i + \overline{\rho}_{ipm}^{mw} + \overline{\mu}_{ipm}^{mh} + \epsilon_{ipm} \tag{3}$$

Y_{ipm} is a measure of marks, either overall score, coursework score, or an indicator for meeting a certian threshold. The structure of this model is analogous to Equation 2. θ_1^m represents the reduced-form impact of a one unit change in each component of $\overline{Structure}_{ipm}$, on marks. These are driven by a combination of their impacts on module-level attendance, the productivity of these marginal events conditional on attendance, the impact of timetable characteristics on the student's other study habits, and the productivity of these marginal changes in effort.

4.3 Other uses of time

The BOOST2018 survey data includes self-reported measures of student allocation of time and allows us to consider this question in combination with our main data set of quasi-experimentally assigned timetables. We use data from survey waves 1 and 3. These elicit self-reports of study habits, including the overall time per week they usually study, propensity to cram, and other time investments, including working for pay. We treat this as student-term level data and estimate the following specification:

$$I_{ips} = \theta_0^s + \theta_1^s \overline{Structure}_{ips} + \lambda_p^s + \theta_2^s \mathbf{X}_i + \overline{\rho}_{ips}^{sw} + \overline{\mu}_{ips}^{sh} + \epsilon_{ips} \tag{4}$$

I_{ips} represents student i on programme p's investment in term s; and other variables are the student-term counterparts to the student-module-level variables in Equation 2 and 3. We include programme and term fixed-effects.

In all specifications for attendance and marks, we weight observations such that each individual has an equal weight, each module within an individual has equal weight, and each event within a module has equal weight. Results are not significantly or qualitatively different using an unweighted specification. In specifications using survey data, we use non-response weights to weight observations to the characteristics of the estimation sample for attendance and academic performance.

4.4 Validity of random assignment

Our primary specification compares students enrolled in the same programme and module, but whose timetables differ due to the random assignment of group events. It assumes students' characteristics are not systematically correlated with their timetables. We test the assumption of conditional random assignment of students to courses using the following models that account for different levels of aggregation and various threats to validity:

$$Structure_{ipmt} = \gamma_0 + \gamma_1 \mathbf{X}_i + \rho_w + \mu_h + \lambda_p + \tau_m + \upsilon_{ipmt} \tag{5}$$

We first focus on the student-event level. Variables are analogous to above, and we cluster at the student level since this is the level at which timetables are assigned and at which individual characteristics $\mathbf{X}_i$ vary.

In the top panel A of Table 3 we regress the *daily structure* characteristics on individual characteristics, with programme plus module fixed-effects, Our test for quasi-random assignment is the F-statistic for joint significance of all the individual characteristics shown in the table, plus (omitted only for reasons of space) the student's entry university qualification type and quintile of standardized university entry qualification scores.

We exclude from this calculation of joint significance the indicator for whether the student lives off campus, since these students are permitted to request timetable changes. We note that off-campus residents have more events in longer back-to-back sequences, as indicated by the positive coefficient on this variable in Column 3. This may reflect an ability of off-campus residents to request events in back-to-back sequences that are convenient for their longer commutes. In Table 4 we replicate all the tests shown in Table 3, for the campus-resident population only.

After correcting for multiple hypothesis testing, we fail to reject F-test of joint non-effects in any column, with just a marginally 10%-level significant unadjusted F-statistic for the *Later in Back-to-Back* column in Table 3, and no such concerns in Table 4. This supports the claim of conditional random assignment among students enrolled in the same programme and suggests that there not meaningful correlations between student timetables and their background observable characteristics.

The lower panels of Tables 3 and 4 test the quasi-random assignment using different levels of aggregation. Individual coefficients are omitted for reasons of space, with just the F-statistic and p-values reported. Panel B reports test statistics where the equation has been aggregated to the student-module level and in Panel C we aggregate to the student-term level.

We find only a single jointly significant association of individual characteristics with any *daily structure* characteristic across all of the person-event, or person-module, and person-term level of aggregation, and a single significant association at the person-level (and then only at the 10% level, disappearing after adjusting for multiple testing). This further supports our assumption of quasi-random assignment to timetables.[13]

These tests cannot completely ensure an effective natural experiment. There may still be endogenous correlation among module and event characteristics and timetables. We formally investigate this with a further set of balance checks, in Table 5, which estimates a version of Equation 5 with module and event-level characteristics, Mod_{mt} replacing student ones. We cluster standard errors instead at the event level, because the characteristics Mod_{mt} do not differ across students assigned to attend the same event. These characteristics include: the number of registered students for a module, the share of contact hours on the module that are of the same type as the present event (which may be a proxy for the relative importance of a particular event), the relative size of the group (compared to an even allocation of students registered for the module), the weighting given to coursework (versus examinations) in calculating marks, and whether the course is compulsory or core. Table 5 again shows no jointly-significant association of module characteristics with timetable characterisics, and only one statistically significant coefficient, and only at the 10% level, from the 24 coefficients shown.

This demonstrates a lack of selection on observable module and event-level characteristics,

[13]We additionally tested for balance, including our measures of the Big 5 personality traits. Across the board, p-values were similar or slightly higher and so we are confident that student timetables are not correlated with measurable personality traits.

but we acknowledge that the bias due to unobservable characteristics may remain a concern. In particular, we do not directly observe instructor quality. If more senior or higher quality staff are somehow scheduled to teach at more favourable times for student attendance and performance, our coefficients estimating impacts of time-of-day or day-of-week may be biased. Those are the salient timetable features for any instructor. This concern only applies to group events, because we include module fixed effects in all our specifications, and all students registered on a module are assigned to the same instructor (or sequence of instructors) for all whole-module events. If such a selection exists, it is unlikely to bias estimates related to $\overline{Structure}_{ipm}$, which is student-specific and varies within each event. Further, in Table 5 we show no significant or materially important association of Relative Teaching Group Size with any of our timetable characteristics. (A one unit increase in Relative Teaching Group size would represent, for example, switching from a group event with half the average group size for events of that type on the module to 1.5 times; or about 12 standard deviations of this variable). Larger teaching groups may be a function of students being moved between groups to accommodate timetabling clashes; which is outside the control of both the student and instructor; but also students invoking exceptional circumstances to request a change. The coefficients indicate no evidence that any of our schedule characteristics are correlated with this or any other unobservable characteristics that would make them more popular for students to switch into or out of.

5 Results

5.1 Attendance and marks

Table 6 shows our overall estimates of timetable impacts on attendance and marks. Estimates on attendance at the student-event level (Equation 1) are in Columns 1-3. Attendance at the student-module level (Equation 2) is shown in Columns 4-6. Estimates on marks at the student-module level (Equation 3) are shown in Columns 7-9. For each model, the three columns vary the vector *Structure* to check for robustness to different specifications. All models include a control for an *Only* event in the day, *start-time*, and *day-of-week*. These are dummy variables in the event-level model and shares in module-level models. The impact of *Back-to-Back* and *Cumulative* events are incorporated in three different ways. The first column of each model (Columns 1,4,7) includes a control for whether or not an event is in a back-back sequence (*Back-*

to-Back Event) and does not include *Cumulative hours*. The second specification (Columns 2,5,8) adds in *Cumulative hours* and the third (columns 3,6,9) separates out the *First of Back-to-Back* and *Later in Back-to-Back* events, due to their hypothesized differential effects on marks. Overall, when considering the different versions of our *Structure* vector, the main coefficients of interest are not meaningfully changed and we focus on the interpretation of the middle (Columns 2,5,8) going forward as our preferred specification. Table A1 considers our main results under alternative standard error clustering.[14]

At the event-level (Column 2), student attendance decisions are meaningfully influenced by numerous aspects of the timetable. Students are less likely to attend *Only* events by 0.9pp. This could reflect the fixed-cost of commuting or a desire to have a "day off". *Back-to-Back* events, meanwhile, increase attendance at the event-level by 1.5pp. The relative efficiency of these events, or the perceived high cost of missing consecutive events leads students to attend at above-average rates. To our knowledge, we are the first to document these particular causal links between timetables and attendance. Using the timetables from Figure 2 as an example, the two students enrolled in the same Tuesday 1300 Lecture have a difference in expected attendance of 2.4pp due to the event being an *Only* event for one student and a *Back-to-Back* for the other.

Time-of-day and day-of-week also impact attendance. Attendance is notably lower in early-morning classes relative to all others (5.8-9.1pp), consistent with Arulampalam *et al.* (2012). Monday is the best-attended day of the week and Friday the worst (5pp lower than Monday).

Module-level estimates in Column 5 examine how timetables affect overall attendance across all events in a module. To compare Columns 2 and 5, consider two points. First, in the typical case of two repeating weekly events per module, these coefficients could be divided by two to obtain the effect of a given weekly event being *Only* or *Back-to-Back*. Second, the aggregate model also reflects substitution on the part of students across events in the same module. Here, *Only* events show an interesting pattern. The sign of the coefficient on *Only* events switches from negative in Column 2 (-0.92pp) to positive in Column 5 (2.8pp). So while students attend *Only* events less frequently, they compensate for that missed attendance by attending the other

[14]Specifically, it estimates our preferred specification with standard errors clustered at the student $\times$ weekly-event level (for attendance at the event level) and at the student $\times$ module level (for module-level attendance and marks). One 10%-significant coefficient of a scheduling characteristic loses significance (for *Only* events on event-level attendance). However, in our context, in which we observe the whole population of interest (all clusters and all units within each cluster), inference does not need to be corrected to reflect any sampling error exacerbated by clustering, so our standard errors are likely already conservative (Abadie *et al.*, 2023). Inference elsewhere is unaffected.

events in that module at an increased rate, resulting in their overall attendance for the module being higher-than-average. We interpret this as strategic and deliberate time use choices on the part of students. Skipping an individual *Only* event provides a perceived benefit (no commute or a day with no events), but students ensure they do not miss the other weekly event(s) for that module.

Other timetable features (*Back-to-Back*, start-time and day-of-week) have module-level estimates in the same direction to their event-level ones. *Back-to-Back* events increase attendance at the event itself and this passes through to the module-level. This is consistent with students not reducing their attendance at the other weekly event(s) for that module.

Overall, we show strong causal evidence that timetables impact attendance choices.[15] Being assigned to a group event with a "high" expected attendance compared to a "low" one is predicted to have attendance impacts in line with moving up a decile or more in average attendance (see Figure 4). We document a particularly interesting pattern on *Only* events that we believe is students using strategic substitution. Another takeaway from these findings is that there are timetable features that can be built-in to increase a programme or university's overall attendance. Multiple events scattered across a day result in absolute lower attendance than two or three events scheduled in sequence.

Next, we focus on how timetables impact marks, Column 8. Broadly, there is not a consistent pattern between impacts on attendance and marks. *Only* and *Back-to-Back* events, which both have significant impacts on attendance at the event- and module-level do not show any significant impact on student marks. This could be consistent with the productivity of attendance at marginal events being very small, as we might expect for *Back-to-Back* events when students are more likely to be fatigued, but could also result from depreciation of learning between attendance and assessment. It is also consistent with students substituting marginal attendance for study time devoted to the same module, with the net effect on marks depending on both the hours reallocated and the relative productivity of attendance and self-study.

Altogether, findings suggest that students are not systematically worse off, on average, when timetable structure gives them scope to miss events they may perceive as lower-productivity.

[15] In Appendix Table A2, we discuss and simulate the potential bias introduced by the practice of students being recorded as attending, for example, because a friend has swiped in on their behalf when they have not done so. This would lead to systematic over-reporting of attendance levels. However, our simulations show that even under quite extreme assumptions about *selective* measurement error in relation to the timetable characteristics, the directions of all our findings remain unchanged.

These results are more in-line with papers that do not find an association between attendance and marks (Bratti & Staffolani, 2013; Kapoor *et al.*, 2021) than with the numerous papers that show a benefit of attendance.

For *start-time* and *day-of-week*, we do see significant impacts on marks, but the coefficient patterns do not point towards attendance being the driving mechanism. Time-of-day is known to have a direct impact on learning above-and-beyond attendance and our results are consistent with the literature's consensus that afternoon increases achievement (Carrell *et al.*, 2011; Diette & Raghav, 2017; Dills & Hernandez-Julian, 2008; Lusher & Yasenov, 2018; Williams & Shapiro, 2018). In our results, all three *start-time* categories show higher attendance relative to early morning classes, but only the late afternoon classes show positive impacts on marks. For *day-of-week*, students attend classes at the highest rate on Mondays and the lowest rate on Fridays. Yet students with a Friday event earn marks that are insignificantly different from their counterparts with Monday events. Meanwhile, students with middle-of-the-week events - which are attended at a rate in between Mondays and Fridays - do earn lower marks relative to students with Monday events. These results cannot identify the precise mechanism causing *day-of-week* to impact marks, but it is unlikely to be their impact on attendance, since in this case we would expect stronger impacts of Friday events relative to midweek ones.

We further explore how timetables impact marks in Table 7. Each column uses an alternate measure of marks as the outcome. The first column replicates Column 8 from Table 6. Columns 2 and 3 use an indicator outcome for whether the key marks thresholds of 70 (First Class) or 60 (Upper Second Class) are achieved.[16] These provide some tentative evidence that there is a detrimental impact of being taught at the end of days with a heavy cumulative load on marks, but only concentrated towards the top of the distribution. There is no evidence of for *Only* or *Back-to-Back* events having such an impact. Midweek events are consistently detrimental.

Columns 4-6 use only the portion of a student's mark attributable to their coursework (i.e. excludes exams). Coursework is potentially more sensitive to timetable, attendance, and productivity conditional on attendance, because it is completed during or immediately after the term in which the module is taught. Hence, there is less scope for these impacts to depreciate or to be offset by revision or exam practice in the intervening period between when the module

[16]The other important threshold is the module pass mark of 40. However, with an overall student-module pass rate of 95% and high incidence of *all* students on a module passing, models using this outcome lack meaningful (conditional) variation in both the explanatory and dependent variables.

is taught and the summer exam period, for which we do not have module-assignable data. However, none of the coefficients in Column 4 are statistically different from those in Column 1. This suggests that the same mechanism that leads to a lack of pass-through to marks overall is at play within the term as well as beyond.

5.2 Reallocation of effort

We are interested in better understanding why timetables strongly impact attendance, but have inconsistent or non-existent resulting impacts on marks in our setting. We are unable to identify directly marginal productivities of attendance, study time, and other learning inputs. However, we do have the data to investigate the extent to which our findings are consistent with reallocation of effort (i) across modules (in Table 8) and (ii) between attendance and other uses of time recorded in survey data (in Table 9).

One mechanism that would attenuate the effects of timetable characteristics both on attendance and marks is students' ability to reallocate effort across modules. If students give higher priority to attending modules that are prerequisites for future coursework or central to their intended degree pathway, they may compensate for inconvenient scheduling by reducing attendance or study effort in less essential modules. The most likely modules to be deprioritised would be students' optional modules, those that do not specifically need to be taken for the student's intended degree programme, and will not not be pre-requisites for or complements to material in students' second and third year modules.[17] By contrast, compulsory modules leave less scope for deprioritisation.

In Table 8 we present results for two restricted samples. In Columns 1-4 we drop all observations pertaining to optional modules. Note that we retain the timetable characteristics for the remaining observations as calculated from these students' full timetables.[18] Impacts on attendance in (Columns 1-2) compare with Table 6 (Columns 2,5) and do not materially

[17]In separate results, we have descriptive evidence supporting students' deprioritisation of optional modules. A fixed-effect (student or module level) regression of attendance and marks on an optional module dummy shows that attendance is 4.7pp lower and marks are 1.4 points lower for optional modules. Within modules, attendance is 3.8pp lower and marks 1.9 points lower among the students for whom that module is optional versus those taking it is as core or compulsory. The attendance difference clearly suggests lower effort, on average, while the marks difference may also represent lower comparative advantage in optional modules.

[18]Every student is retained in these specifications, and, as with our main specifications, each person is given an equal weight, and within each person each non-optional module used in the regression is given an also an equal weight. This ensures that subject areas with fewer optional modules are not given a higher weight. We thus avoid the risk conflating the impact of focusing on non-optional modules, with heterogeneity of impact by field of study.

shift. When considering overall marks and coursework marks in Columns 3-4, the coefficient on *Back-to-Back* events increases from approx 0.8 to around 1.3 and just surpasses statistical significance when looking at coursework marks. This suggests that, conditional on attending, the productivity of attendance at *Back-to-Back* events is lower for the excluded optional modules, possibly because concentration in class is lower or because students invest less in complementary study time.

In Columns 5-8 we drop students taking any optional modules. This means we retain students taking degree programmes with a full slate of compulsory or core first-year modules and no space for students to select optional modules.[19] Since, as discussed in section 2.2, optional modules may be chosen after the timetable is published, this specification also provides a robustness check for a population with a wholly-exogenously assigned timetable. We cannot entirely disentangle the impact of the change in optional status of modules with sample composition by subject. This sample restriction eliminates History, Philosophy, and Psychology students entirely from the sample, and concentrates the estimation more heavily in Biology, Business, Computer Science, Languages, Law, and Maths. In Column 6 we see the positive impact of *Only* and *Back-to-Back* events on module-level attendance is intensified, with coefficients approximately doubling in magnitude. The positive impact of *Back-to-Back* events on overall marks also increases and becomes significant at the 10% level, which is consistent with the greater dose of attendance not being wholly offset by greater fatigue. The negative coefficients on *Cumulative* also approximately double in magnitude, becoming significant at the the 1% level for overall marks and 5% level for coursework. A greater effort to concentrate results in higher fatigue in events later into a heavily-scheduled day.

Our results are consistent both with studies finding null causal effects of attendance on marks in high-autonomy settings—where substitution is feasible (Bratti & Staffolani, 2013; Kapoor *et al.*, 2021), and with studies identifying positive effects in single-module or more constrained environments (Arulampalam *et al.*, 2012; Pope, 2015; Williams & Shapiro, 2018), where students have fewer opportunities to offset reduced attendance through alternative learning inputs and experience greater fatigue.

Table 9 considers impacts on student's general time allocation outside of the classroom. It

[19] For 96% of degree programmes, either all students either have zero optional modules (who we retain here) or none do (which we drop). Here we also drop 23 students registered on the other 14 degree programmes who somehow take an optional module in defiance of this assignment.

uses the survey component of BOOST2018 and shows the impact of the timetables on study time, cramming, and engagement in working for pay. These are measured at the student-term level, corresponding to Equation 4, and for comparability in Column 1 we show a specification for attendance at the term level. Although we lose precision, the positive signs on *Only* and *Back-to-Back* events match those in Table 6, with the magnitudes inflated.

There are no significant impacts of *Only*, *Back-to-Back* or *Cumulative* events on any of these activities, so these cannot help explain why the impacts on attendance do not pass through to marks. What we do see is that events scheduled later in the day significantly reduce study time. Combined with the small positive effects of later events on marks documented in Table 6, this lends further credibility to later-in-day events being good for both attendance and for in-class productivity, conditional on attendance.

The significant detrimental impact of midweek events on marks in the modules scheduled then, compared with both Monday and Friday events, could not be attributed to attendance rates, since these are higher for midweek events than for Fridays. There is also no evidence that this can be explained by lower total study time (particularly in contrast to Friday events), differing study habits, or working for pay.

A potential explanation is that Friday non-attendance is more likely to be planned, for example, to enable a longer weekend, than is midweek non-attendance. This is consistent with evidence from Clifton-Sprigg & James (n.d.) who present evidence of higher absence rates on Fridays ahead of short vacations or weekends followed by a public holiday. Analogously to our inference that students skipping an *Only* event make up for this with increased attendance at other events on the module, students skipping a Friday event may be more likely to plan to substitute for this with private study, whereas this may not happen with an unplanned midweek absence. The difference between planned and unplanned absence may occur in combination with the impact of day of week on productivity and retention, conditional on attendance. Higher productivity of Monday than midweek attendance is consistent with better cognitive performance the day after a break (Glaser & Insler, 2022). Proximity to the weekend also means better opportunities for timely preparation, recapping, or retrieval of material for Monday and Friday events compared with midweek ones (Carpenter *et al.*, 2022; Reinke, 2018).

Although the *daily structure* of students' timetables do not impact students' ability to work for pay, it is intuitive that that those whose events are predominantly first thing in the morning are more able to take up employment, hence the stable negative coefficients on the later time-of-day dummies. For our heterogeneity analysis, we retain study time in our analyses, as a potential driver of impacts on marks for sub-groups of the population.

5.3 Heterogeneous responses

Tables 10-11 and Figures 5-6 examine our main results for attendance, study time, and marks, broken down by event and student characteristics that we would expect, *a priori* to drive differential responses by students, and hence have differential impacts on performance.

Table 10 presents results for our main specification excluding International students from our estimation sample. International students have their engagement with their course of study more strictly monitored in order to ensure compliance with visa conditions, so these results represent estimates for the population with the highest genuine autonomy over attendance and study and no explicit incentive to arrange for classmates to swipe on their behalf.

Reassuringly, when International students are dropped, no coefficients for any of our main scheduling characteristics are statistically different from those in the full sample. Taking coefficients at face-value, the larger magnitudes of coefficients on *Only* in the event-level attendance column and at term-level in the study column, is consistent with domestic students treating attendance at these events as discretionary and taking advantage to have a whole day off. Since sharing student cards across multiple days is difficult to coordinate, we are confident this represents genuine attendance behaviour.

Table 11 assess heterogeneity by event type. This relates to whether students are expected to learn through active interaction. We break these down into lectures, labs and other group teaching. The table shows the effects of *Only* and *Back-to-Back* events on lectures (the baseline group), and the interaction term shows the difference in the impact of this timetable characteristic between the specified group and baseline.[20] A dummy for the specified group is always included elsewhere in the model. The model is not fully interacted, meaning that the effects of all other covariates (including *Cumulative Hours*, start-time and day-of-week) in the model are assumed to be the same across groups.

[20] We carry this out interaction *after* collapsing to module (or term), meaning that the coefficients for these aggregated specifications are deliberately interpreted as relating to the impact of daily structure in modules with a greater or lesser share of events that are labs.

The most striking finding is that while students are significantly more likely to attend *Back-to-Back* lectures, relative to this, they are significantly less likely to attend lab events (-5pp) and marginally less likely (-1.6pp) to attend other group events. This is consistent with students anticipating fatigue for lab events scheduled back-to-back, such that this outweighs their relative convenience. This interpretation applies at the event-level, and is also reflected in overall attendance at the module-level.[21] Moreover, although not significant, the reduction in study hours and in marks in response to having back-to-back events in modules with labs, suggests that the overall coefficients are masking important heterogeneity. A similar picture emerges for *Only* events, with positive and large, though again insignificant, coefficients on this interaction term for module-level attendance and term-level study.[22] The common direction of attendance, study and marks here is suggestive of complementarities between study and attendance being more important for the predominantly-quantitative modules taught through labs, than in other fields.[23] This further helps explain why prior studies focused on a single quantitative module (Andrietti & Velasco, 2015; Arulampalam *et al.*, 2012; Dobkin *et al.*, 2010) have found causal benefits of attendance while those looking university-wide (Bratti & Staffolani, 2013; Kapoor *et al.*, 2021) have not.

Heterogeneity by other student characteristics are summarised in Figures 5-6. The figures show point estimates and 90% confidence intervals for the marginal effect of *Only* and *Back-to-Back* events using analogous models to that used for event type, above.

The top two rows of Figures 5-6 show marginal effects by residence type. Off-campus students represent 12% of the enrolled population and face higher fixed-costs of attending university on a given day, and are more constrained in the space available to them between classes.

Figure 6 clearly shows that off-campus residents' attendance is highly positively responsive to *Back-to-Back* events, consistent with our hypothesis that these students are more responsive

[21]The large coefficient of 21.7 in Column 2 should be interpreted in light of its low average value of 0.037. A one standard deviation (0.084) increase in this characteristic is predicted to reduce attendance by 1.8 percentage points.

[22]These findings also provide further evidence that one-sided measurement error owing to swiping for non-attendeeds is not a major issue. This practice should be easier to carry out in lectures than in labs or group events where the discrepancy between recorded attendance and students' (lack of) engagement is more likely to be noticed. We would expect this to result in a larger recorded negative impact of an event being *Only* on attendance at Labs than lectures, but this is not the case. On the contrary the interaction term of *Only Event* × Lab in both the event-level and module-level columns of Table 11 is positive and large.

[23]For example, if we classify as quantitative all modules taught in the departments of Biology, Business, Computer Science, Economics, Maths or Psychology, then 12.7% (1.8%) of quantitative (non-quantitative) teaching events are labs; and 65% (17%) of quantitative (non-quantitative) modules conduct at least some teaching in labs.

to the efficiency of their timetable. This effect is seen at the event level and carries through to the module level. Off-campus students do not appear significantly more deterred from attending *Only* eventsthan other events. In Column 3 of Figure 5 our results suggest (p-value of 0.15) that *Only* events reduce study for off-campus students. If the student has 10 events per week, the coefficient is consistent with an extra *Only* event reducing study time by 1.23 hours per week, which is a plausible duration for a round-trip commute to crowd-out study time. Like our main result, there are no corresponding significant impacts on marks.

Rows 3 and 4 assess heterogeneity by students' conscientiousness, which we argue is the most relevant measured noncognitive trait affecting students' cost of attendance or substituting study for attendance. We restrict the sample to study participants who provided responses to the battery eliciting the Big 5 personality traits, and define conscientious students as those with conscientiousness above the sample median.[24] Across both figures, conscientious students show no significant impacts of timetable structure. Non-conscientious students do significantly reduce attendance and study time in response to having *Only* events and they drive the positive attendance effect of *Back-to-Back* events. For study time, the marginal effect of *Back-to-Back* for conscientious students is positive and significantly different from non-conscientious (but not from zero), providing some suggestive evidence that they increase their relative study time, making use of how *Back-to-Back* events result in more uninterrupted time before and after the day's timetabled events. Both these findings indicate that the structure of the timetable again has meaningfully different impacts on different students' effort allocations according to their characteristics. However, once again these timetable features do not have a significant overall or differential effect on marks.[25]

Finally, in rows 5-7 of Figures 5-6 we assess heterogeneity by the higher education experience of the students' parents. This serves as a proxy for the student's socio-economic status, and for access to information about teaching and assessment types and approaches to independent study at university. Parental education is also positively correlated with living on campus. Together

[24] Conscientiousness was measured as the sum of "I am someone who does a thorough job", "... does things efficiently" and "tends to be lazy", all elicited on a fully-labeled 7-point scale from Strongly Disagree to Strongly Agree, with the last item reverse-coded. Table A3 shows that conscientiousness is the only one of the Big 5 traits to correlate with all four of our main outcomes, with coefficients at least twice as large as the others.

[25] For completeness we undertake further assessment of heterogeneity by the other Big 5 personality traits in Appendix Figures A1 and A2. Here, strikingly, those with high levels of neuroticism, extraversion, agreeableness and openness to experience are all less response to back-to-back timetabling at the event level than those with lower levels of these traits. This intuitively may reflect the psychic costs of *not* attending, for neurotic students; and lower psychic costs of attendance, and hence relative unimportance of convenience, for the others. However, like conscientiousness, none of these lead to any significant differential effects on marks, but none show any significant differential effects on study, a behavioural response which for conscientiousness were quite striking.

these factors may mean students who have a parent with a degree more resilient to the impacts of an inconvenient timetable. Most noticeably, the results show that those without a parental degree are not more likely to miss an *Only* than a default event, and have considerably higher attendance in modules with more *Only* events. Those with a parental degree are more happy to skip these events, and almost exactly make up for it in module-level attendance. This provides some suggestive evidence for those with a parental degree being more strategic, or confident in their entitlement to miss inconvenient events, in their response to the timetable. However, again there are no significant differences in effects on study or on marks.[26]

6 Discussion and conclusion

We use linked timetable, daily attendance, and administrative data from a representative public UK university to understand the impacts of timetable structure on student decisions and achievement. We exploit quasi-random assignment to timetables of students enrolled in the same degree programmes and taking the same modules and show balance tests supporting our pseudo-experimental setting. Our primary model is supplemented with time-use and survey data that allows us to consider mechanisms such as conscientiousness as drivers of our results.

We identify four related findings. Each of these is either novel to the field or is strengthened by our granular data and our ability to observe students across a representative set of programmes.

First, we show that student daily attendance choices are dependent on their timetable structure and timing. *Only* events decrease event-level attendance, while *Back-to-Back* ones increase it; both are novel results. Time-of-day and day-of-week have sizeable attendance impacts, broadly consistent with prior literature (Arulampalam *et al.*, 2012; Dills & Hernandez-Julian, 2008). A university looking to increase absolute attendance should focus on later start times and prioritizing *Back-to-Back* events. They are more convenient to attend and raise event-level and overall module-level attendance, especially for commuting students. We also see lower attendance for Friday events, and while four-day school weeks have shown some promise (Anderson & Walker, 2015), we cannot be sure of the equilibrium effects of reducing or eliminating Friday events.

[26] We undertake further assessment of heterogeneity by sex, reported in Appendix Figures A1 and A2. Despite females attending significantly more, engaging in significantly longer hours of private study, and achieving significantly higher marks, we find no significant differential effects.

Second, students offset marginal non-attendance at some events by increasing attendance at other events. In particular, we observe patterns consistent with students missing some sessions while ensuring they attend other sessions, so that module-level attendance can be maintained even when event-level attendance falls. We are not the first to document that student's are strategic in their time-use decisions (Delavande *et al.*, 2021), but are the first to causally document this sort of strategic attendance substitution across events. Our heterogeneity results suggest the 'right' timetable may differ depending on the student. For example, we show that *Only* events reduce study time and event-level attendance for students with below-median conscientiousness meaningfully more than ones with above-median levels, indicating differential reallocation responses.

Third, we contribute to understanding the link between attendance and achievement. Attendance is clearly positively associated with achievement, but whether this relationship is causal is less clear. In prior studies that consider autonomy across a representative range of programmes (e.g. Bratti and Staffolani, 2013; Goulas et al., 2023, Kapoor et al 2021), attendance did not causally improve marks. Meanwhile, studies focused on a single, typically economics, module (Andrietti & Velasco, 2015; Chen & Lin, 2008; Cohn & Johnson, 2006) have found an impact.

Our results support both themes. In our overall sample, timetable structure shifts attendance, but these changes do not consistently pass through to marks. The reallocation patterns identified above provides a natural explanation for why sizable attendance effects do not necessarily translate into achievement gains: timetable-induced changes in attendance may operate on the margin, affecting sessions with low marginal returns net of the productivity of what students would do instead of attending. We cannot disentangle the marginal productivities of attendance and study driven by timetable structure, but our survey evidence shows little systematic effect of timetable structure on total study hours, cramming, or paid work. We find suggestive evidence of complementarities between attendance and study being more important in lab-based (typically STEM/quantitative) modules, where the relationship between timetable structure, attendance and achievement appears tighter.

Fourth, we see an impact of cumulative daily course loads on marks for students taking no optional (i.e. exclusively compulsory) modules, a pattern suggestive of cognitive fatigue in settings where students have less scope to deprioritise modules. This is consistent with the null impacts of timetable structure on marks that we find in general, being particular to multi-module settings in which students have high autonomy over the relative and absolute levels and forms of effort they devote to each. Our robustness checks using alternative performance measures (coursework versus overall marks) and restricted samples excluding optional modules are consistent with module prioritisation playing a more important role.

Nevertheless, even when we restrict the analysis to the sub-population with reduced autonomy, we find that the effect of timetable structure on achievement is smaller in magnitude than studies where students have fuller timetables and compulsory attendance (Pope, 2015; Williams & Shapiro, 2018). Our setting has comparatively sparse timetables (an average of 9 weekly events, 2-3 in-person hours per day), representative of much of higher education. Cognitive fatigue developing over the course of a heavy day is certainly possible, but likely compounds with higher weekly event loads and is not a major concern here.

Our results have implications for administrations, advisers, and students looking to set themselves up for success. Later start times and compact, but not-overfilled schedules are good for attendance. Further, the autonomy in time-use of university students is similar to that of many professional positions, especially in the growing hybrid and work-from-home era (Bloom *et al.*, 2014). It features a mix of commutes, scheduled meetings, self-directed work, extended deadlines and opportunities for procrastination. Our findings are in line with studies measuring the impacts of flexibility and autonomy on productivity in the labour market (Beckmann *et al.*, 2017; Boltz *et al.*, 2023).

References

Abadie, Alberto, Athey, Susan, Imbens, Guido W, & Wooldridge, Jeffrey M. 2023. When Should You Adjust Standard Errors for Clustering? *The Quarterly Journal of Economics*, **138**(1), 1–35. DOI: https://doi.org/10.1093/qje/qjac038.

Ackerman, Phillip L., & Kanfer, Ruth. 2009. Test length and cognitive fatigue: an empirical examination of effects on performance and test-taker reactions. *Journal of Experimental Psychology. Applied*, **15**(2), 163–181. DOI: https://doi.org/10.1037/a0015719.

Anderson, D. Mark, & Walker, Mary Beth. 2015. Does Shortening the School Week Impact Student Performance? Evidence from the Four-Day School Week. *Education Finance and Policy*, **10**(3), 314–349. DOI: https://doi.org/10.1162/EDFP_a_00165.

Andrietti, Vincenzo, & Velasco, Carlos. 2015. Lecture Attendance, Study Time, and Academic Performance: A Panel Data Study. *The Journal of Economic Education*, **46**(3), 239–259. DOI: https://doi.org/10.1080/00220485.2015.1040182.

Arulampalam, Wiji, Naylor, Robin A., & Smith, Jeremy. 2012. Am I missing something? The effects of absence from class on student performance. *Economics of Education Review*, **31**(4), 363–375. DOI: https://doi.org/10.1016/j.econedurev.2011.12.002.

Beattie, Graham, Laliberte, Jean-William, Miachaud-Leclerc, Catherine, & Oreopoulos, Philip. 2019. What sets college thrivers and divers apart? A contrast in study habits, attitudes, and mental health. *Economics Letters*, **178(C)**, 50–43. DOI: https://doi.org/10.1016/j.econlet.2018.12.026.

Beckmann, Michael, Cornellissen, Thomas, & Krakel, Matthias. 2017. Self-managed working time and employee effort: Theory and evidence. *Journal of Economic Behavior and Organization*, **133**, 285–302. DOI: https://doi.org/10.1016/j.jebo.2016.11.013.

Bloom, Nicholas, Liang, James, Roberts, John, & Ying, Zhichun Jenny. 2014. Does Working from Home Work? Evidence from a Chinese Experiment *. *The Quarterly Journal of Economics*, **130**(1), 165–218. DOI: https://doi.org/10.1093/qje/qju032.

Bloom, Nicholas, Han, Ruobing, & Liang, James. 2024. Hybrid working from home improves retention without damaging performance. *Nature*, **630**, 920–225. DOI: https://doi.org/10.1038/s41586-024-07500-2.

Boltz, Marie, Cockx, Bart, Diaz, Ana Maria, & Salas, Luz Magdalena. 2023. How does working-time flexibility affect workers' productivity in a routine job? Evidence from a field experiment. *British Journal of Industrial Relations*, **61**(1), 159–187. DOI: https://doi.org/10.1111/bjir.12695.

Bratti, Massimiliano, & Staffolani, Stefano. 2013. Student time allocation and educational production functions. *Annals of Economics and Statistics*, **111/112**, 103–140. DOI: https://doi.org/10.2307/23646328.

Carpenter, S.K., Pan, S.C., & Butler, A.C. 2022. The science of effective learning with spacing and retrieval practice. *Nature Reviews Psychology*, **1**, 496–511. DOI: https://doi.org/10.1038/s44159-022-00089-1.

Carrell, Scott E, Maghakian, Teny, & West, James E. 2011. A's from ZZZZ's? The causal effect of school start time on the academic achievement of adolescents. *American Economic Journal: Economic Policy*, **3**(3), 62–81. DOI: https://doi.org/10.1016/10.1257/pol.3.3.62.

Chen, Jennjou, & Lin, Tsui-Fang. 2008. Class Attendance and Exam Performance: A Randomized Experiment. *The Journal of Economic Education*, **39**(3), 213–227. DOI: https://doi.org/10.3200/JECE.39.3.213-227.

Clifton-Sprigg, Joanna, & James, Jonathan. The 'Friday effect': School attendance over the week. *British Educational Research Journal*, **51**(1), 73–92. DOI: https://doi.org/10.1002/berj.4066.

Cohn, Elchanan, & Johnson, Eric. 2006. Class Attendance and Performance in Principles of Economics. *Education Economics*, **14**(2), 211–233. DOI: https://doi.org/10.1080/09645290600622954.

Cortes, Kalena, Bricker, Jesse, & Rohlfs, Chris. 2012. The Role of Specific Subjects in Education Production Functions: Evidence from Morning Classes in Chicago Public High Schools. *The B.E. Journal of Economic Analysis & Policy*, **12**. DOI: https://doi.org/10.1515/1935-1682.2749.

Cortinhas, Carlos. 2025. Does nudging higher education students improve attendance and does it matter? A quasi-natural experiment. *International Review of Economics Education*, **49**, 100317. DOI: https://doi.org/10.1016/j.iree.2025.100317.

Cotti, Chad, Gordanier, John, & Ozturk, Orgul. 2018. Class meeting frequency, start times, and academic performance. *Economics of Education Review*, **62**(Feb.), 12–15. DOI: https://doi.org/10.1016/j.econedurev.2017.10.010.

Delavande, Adeline, Bono, Emilia Del, & Holford, Angus. 2021. Academic and non-academic investments at university: The role of expectations, preferences and constraints. *Journal of Econometrics*, **2021**(1). DOI: https://doi.org/10.1016/j.jeconom.2020.03.019.

Delavande, Adeline, Del Bono, Emilia, & Holford, Angus. 2022. *BOOST2018: The Ground-Breaking Study of Student Life, 2015-2020: Secure Access. [data collection]*. UK Data Service. SN: 8877. DOI: 10.5255/UKDA-SN-8877-2.

Delavande, Adeline, Del Bono, Emilia, & Holford, Angus. 2025. Imprecise health beliefs and health behavior. *Journal of Health Economics*, **102**, 103003. DOI: https://doi.org/10.1016/j.jhealeco.2025.103003.

Department for Education. 2011. *LSYPE User Guide to the Datasets: Wave 1 to Wave 7*.

Department for Education. 2024. *Data set from Widening participation in higher education: Tariff Groups*.

Diette, Timothy M., & Raghav, Manu. 2017. Does early bird catch the worm or a lower GPA? Evidence from a liberal arts college. *Applied Economics*, **49**(33), 3341–3350. DOI: https://doi.org/10.1080/00036846.2016.1259750.

Dills, Angela, & Hernandez-Julian, Rey. 2008. Course Scheduling and Academic Performance. *Economics of Education Review*, **27**, 646–654. DOI: https://doi.org/10.1016/j.econedurev.2007.08.001.

Dobkin, Carlos, Gil, Ricard, & Marion, Justin. 2010. Skipping class in college and exam performance: Evidence from a regression discontinuity classroom experiment. *Economics of Education Review*, **29**(4), 566–575. DOI: https://doi.org/10.1016/j.econedurev.2009.09.004.

Dolton, Peter, Marcenaro, Oscar, & Navarro, Lucia. 2003. The effective use of student time: a stochastic frontier production function case study. *Economics of Education Review*, **22**, 547–560. DOI: https://doi.org/10.1016/S0272-7757(03)00027-X.

Edwards, Finley. 2012. Early to rise? The effect of daily start times on academic performance. *Economics of Education Review*, **31**(6), 970–983. DOI: `https://doi.org/10.1016/j.econedurev.2012.07.006`.

Feng, Andy, & Graetz, Georg. 2017. A question of degree: The effects of degree class on labor market outcomes. *Economics of Education Review*, **61**, 140–161. DOI: `https://doi.org/10.1016/j.econedurev.2017.07.003`.

Fryer, Roland. 2011. Financial Incentives and Student Achievement: Evidence from Randomized Trials. *Quarterly Journal of Economics*, **126**(4), 1755–1798. DOI: `https://doi.org/10.1093/qje/qjr045`.

Glaser, Darrell J., & Insler, Michael A. 2022. The deleterious effects of fatigue on final exam performance. *Economics of Education Review*, **90**, 102305. DOI: `https://doi.org/10.1016/j.econedurev.2022.102305`.

Goulas, Sofoklis, Griselda, Silvia, & Megalokonomou, Rigissa. 2023. Compulsory Class Attendance versus Autonomy. *Journal of Economic Behaviour and Organization*, **212**, 935–981. DOI: `https://doi.org/10.1016/j.jebo.2023.06.018`.

Groen, Jeffrey, & Pabilonia, Sabrina Wulff. 2019. Snooze or Lose: High School Start Times and Academic Achievement. *Economics of Education Review*, 204–218. DOI: `https://doi.org/10.1016/j.econedurev.2019.05.011`.

Ha, Wei, Ma, Liping, Cao, Yulian, Feng, Qinxue, & Bu, Shangcong. 2024. The effects of class attendance on academic performance: Evidence from synchronous courses during Covid-19 at a Chinese research university. *International Journal of Educational Development*, **104**(Jan.), 102952. DOI: `https://doi.org/10.1016/j.ijedudev.2023.102952`.

Haggag, Kareem, Patterson, Richard W., Pope, Nolan G., & Feudo, Aaron. 2021. Attribution bias in major decisions: Evidence from the United States Military Academy. *Journal of Public Economics*, **200**, 104445. DOI: `https://doi.org/10.1016/j.jpubeco.2021.104445`.

Heissel, Jennifer, & Norris, Samuel. 2017. Rise and Shine: The Effect of School Start Times on Academic Performance from Childhood through Puberty. *Journal of Human Resources*, Apr., 0815–7346R1. DOI: `https://doi.org/10.3368/jhr.53.4.0815-7346R1`.

High Fliers Research. 2014. *The Graduate Market in 2014: Annual review of graduate vacancies starting salaries at Britain's leading employers.*

Jackson, Simon A., Kleitman, Sabina, & Aidman, Eugene. 2014. Low Cognitive Load and Reduced Arousal Impede Practice Effects on Executive Functioning, Metacognitive Confidence and Decision Making. *PLOS ONE*, **9**(12), e115689. DOI: `https://doi.org/10.1371/journal.pone.0119113`.

Kapoor, Sacha, Oosterveen, Matthijs, & Webbink, Dinand. 2021. The Price of Forced Attendance. *Journal of Applied Econometrics*, **36**, 209–227. DOI: `https://doi.org/10.1002/jae.2781`.

Lundberg, Shelley. 2013. Educational Inequality and the Returns to Skills. *IZA Discussion Papers*, **7595**, 1–38.

Lusher, Lester, & Yasenov, Vasil. 2018. Gender Performance Gaps: Quasi-Experimental Evidence on the Role of Gender Differences in Sleep Cycles. *Economic Inquiry*, **56**(1), 252–262. DOI: `https://doi.org/10.1111/ecin.12483`.

Lynn, Peter, & Borkowska, Magdalena. 2018. Some Indicators of Sample Representativeness and Attrition Bias for BHPS and Understanding Society. *Understanding Society Working Paper Series*, **2018**(01).

Mergoupis, Thanos, & Zubrickas, Robertas. 2023. Work experience, information revelation, and study effort. *Oxford Economic Papers*, **76**(2), 495–513. DOI: `https://doi.org/10.1093/oep/gpad015`.

Millimet, Daniel L., & Parmeter, Christopher F. 2022. Accounting for Skewed or One-Sided Measurement Error in the Dependent Variable. *Political Analysis*, **30**(1), 66–88. DOI: `https://doi.org/10.1017/pan.2020.45`.

Montauban, Nicolas. 2025. *Do University Students Attend Class?* Attendance Radar blog, 30th April 2025.

Naylor, Robin, Smith, Jeremy, & Telhaj, Shqiponja. 2016. Graduate Returns, Degree Class Premia, Ability Composition and Higher Education Expansion in the UK. *Oxford Economic Papers*, **68**(2), 525–545. DOI: `https://doi.org/10.1093/oep/gpv070`.

Pope, Nolan. 2015. How Time of Day Affects Productivity: Evidence from School Schedules. *The Review of Economics and Statistics*, **98**(1). DOI: https://doi.org/10.1162/REST_a_00525.

Reinke, Nicole B. 2018. The impact of timetable changes on student achievement and learning experiences. *Nurse Education Today*, **62**, 137–142. DOI: https://doi.org/10.1016/j.nedt.2017.12.015.

Rice, Jennifer King, Croninger, Robert G, & Roellke, Christopher F. 2002. The effect of block scheduling high school mathematics courses on student achievement and teachers' use of time: implications for educational productivity. *Economics of Education Review*, **21**(6), 599–607. DOI: https://doi.org/10.1016/S0272-7757(01)00045-0.

Romer, David. 1993. Do Students Go to Class? Should They? *Journal of Economic Perspectives*, **7**(3), 167–174. DOI: https://doi.org/10.1257/jep.7.3.167.

Sankoh, A.J., Huque, M.F., & Dubey, S.D. 1997. Some comments on frequently used multiple endpoint adjustment methods in clinical trials. *Statistics in Medicine*, **16**, 2529–2542. DOI: https://doi.org/10.1002/(sici)1097-0258(19971130)16:22%3C2529::aid-sim692%3E3.0.co;2-j.

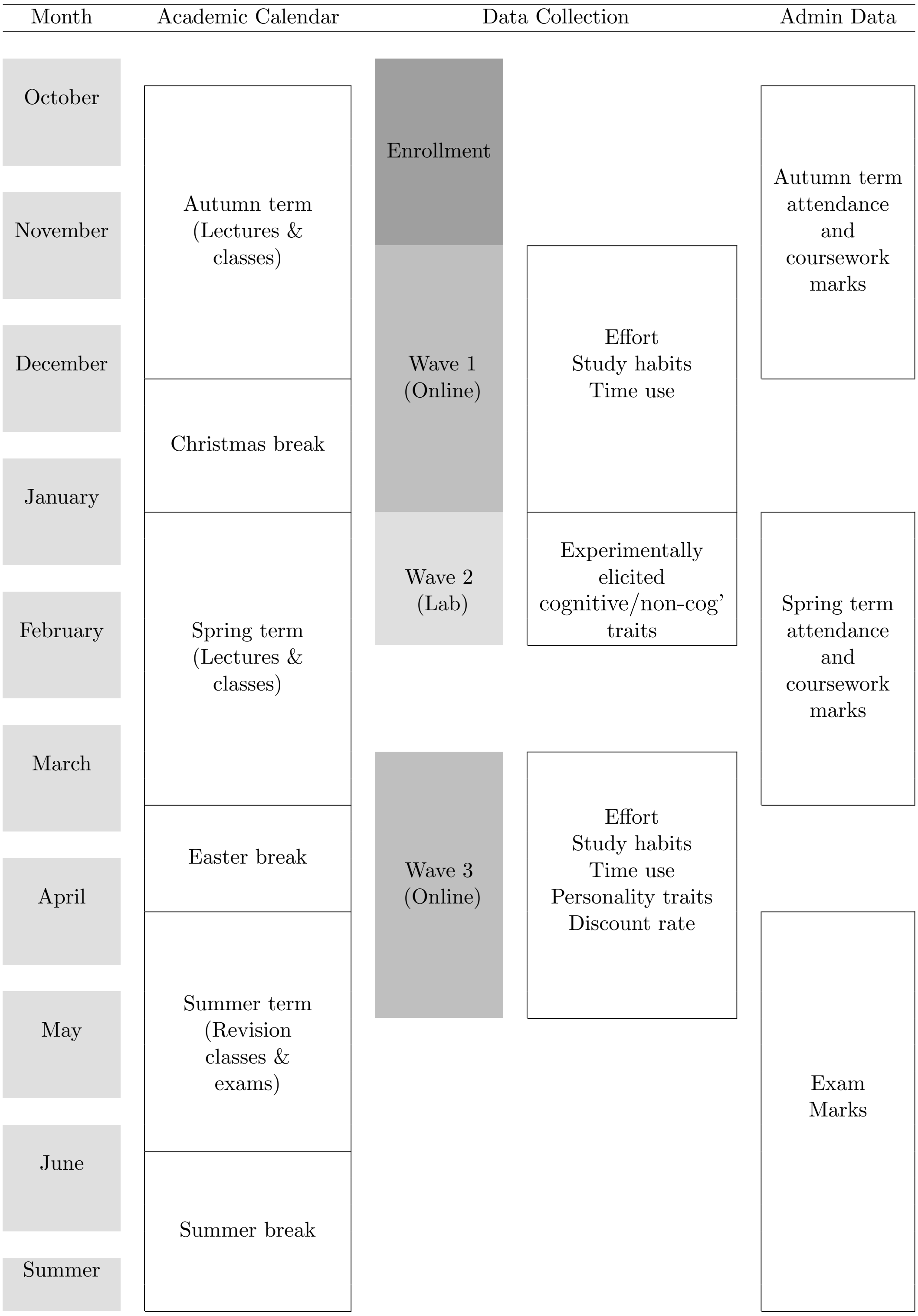
Walker, Ian, & Zhu, Yu. 2011. Differences by degree: Evidence of the net financial rates of return to undergraduate study for England and Wales. *Economics of Education Review*, **30**, 1177–1186. DOI: https://doi.org/10.1016/j.econedurev.2011.01.002.

Williams, Kevin, & Shapiro, Teny. 2018. Academic achievement across the day: Evidence from randomized class schedules. *Economics of Education Review*, **67**, 158–170. DOI: https://doi.org/10.1016/j.econedurev.2018.10.007.

Williams, Tom. 2022. Class attendance plummets post-Covid. *Times Higher Education*.

7 Figures and Tables

Figure 1: Timeline of the Study



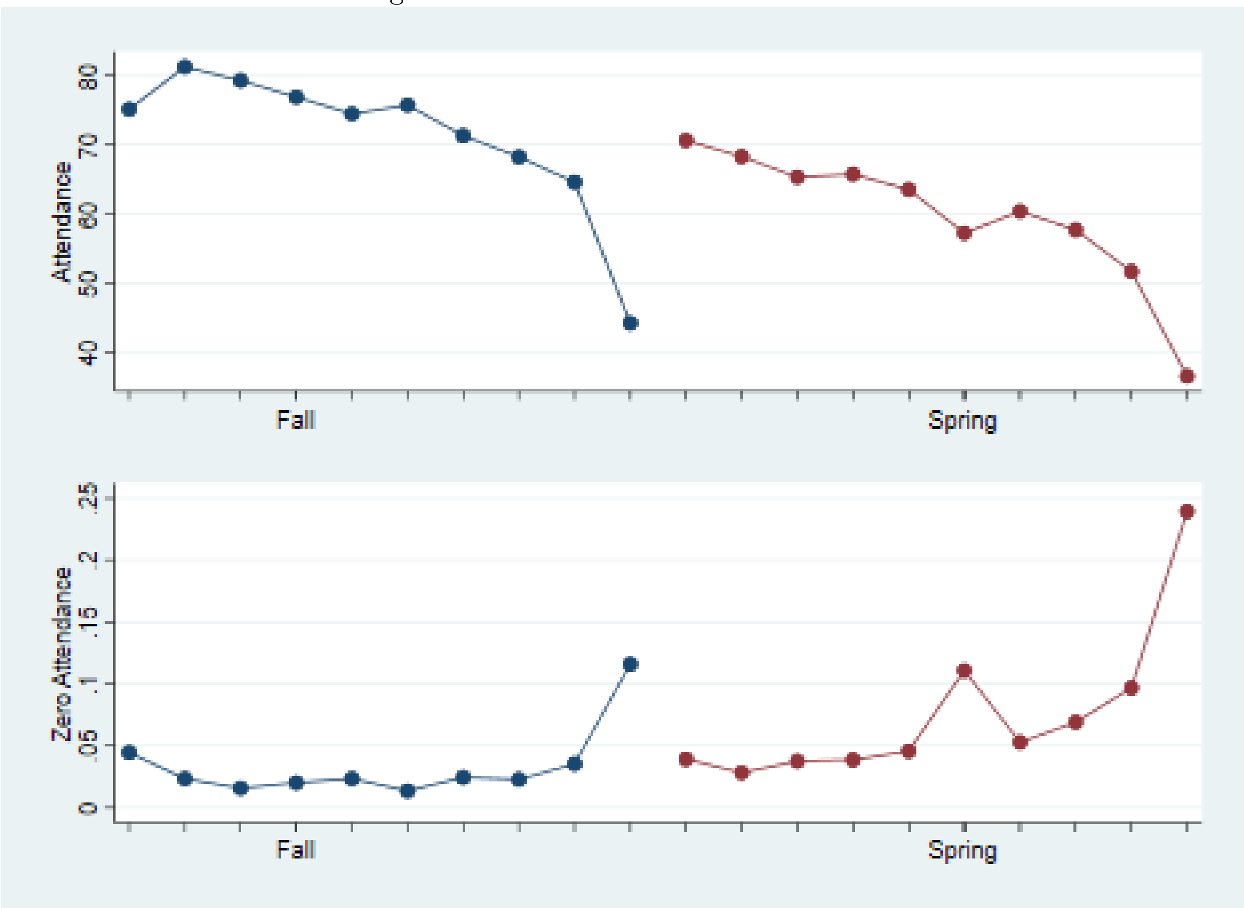
Notes: Representation of the timeline of the first year of data collection.

Figure 2: Example Timetables

Student 1:	**Economics programme**					
	0900	1000	1100	1200	1300	1400
Monday		Maths 0, 0, 0 ,0				Maths 0, 0, 0, 1
		Lecture				Class 1
Tuesday					Micro 1, 0, 0, 0	
					Lecture	
Wednesday	Stats 0, 0, 0, 0		Macro 0, 1, 0, 1	Stats 0, 0, 1, 2	Micro 0, 0, 1, 3	
	Lecture		Class 1	Class 1	Class 1	
Thursday			Macro 1, 0, 0, 0			
			Lecture			
Student 2:	**Economics programme**					
	0900	1000	1100	1200	1300	1400
Monday		Maths 1, 0, 0, 0				
		Lecture				
Tuesday					Micro 0, 1, 0, 0	Maths 0, 0, 1, 1
					Lecture	Class 2
Wednesday	Stats 0, 0, 0, 0		Macro 0, 0, 0, 1		Micro 0, 0, 0, 2	
	Lecture		Class 1		Class 1	
Thursday			Macro 0, 1, 0, 0	Stats 0, 0, 1, 1		
			Lecture	Class 2		
Figures shown are *Only* , *First of Back-to-Back* , *Later in Back-to-Back* , *Cumulative*						

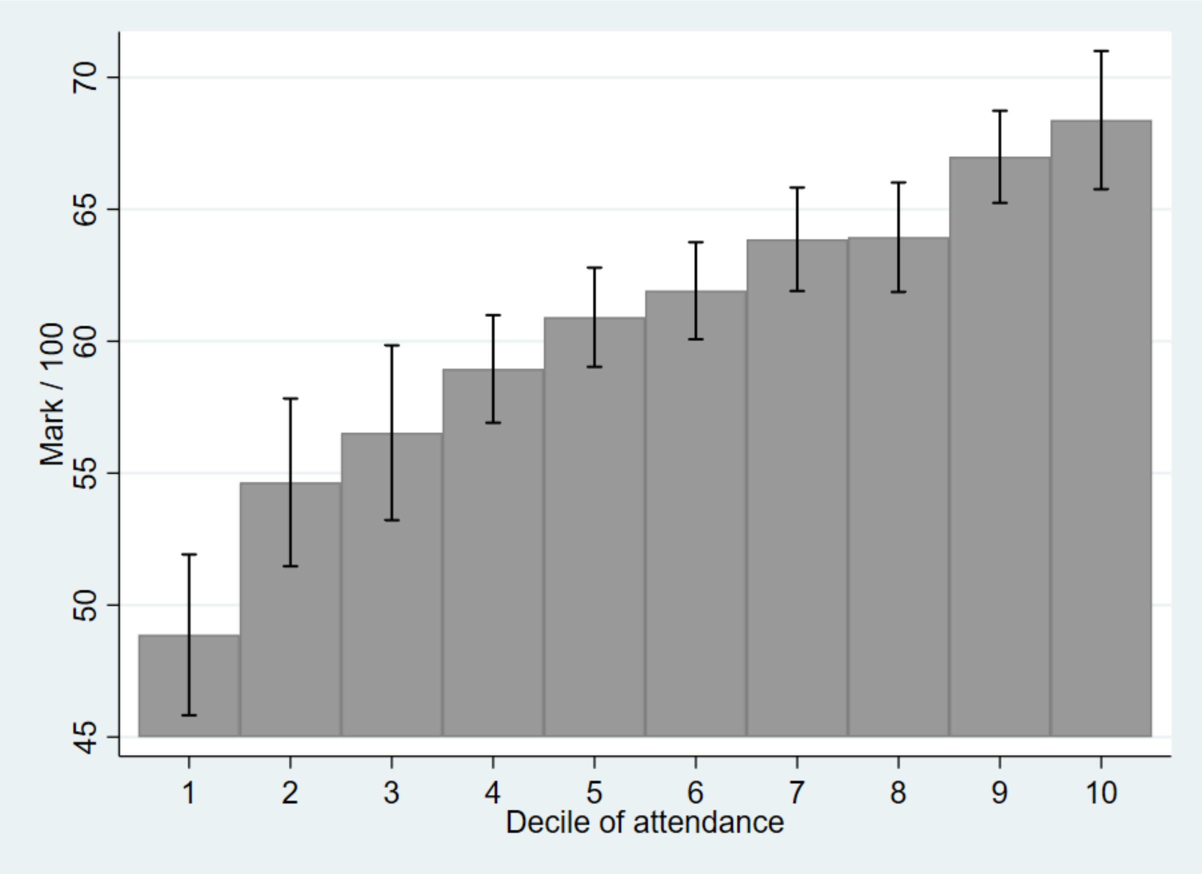
Notes: Shows example weekly timetable for two students. Common shading represents a given module. Figures shown are: *Only* (student's only event on a given day); *First of Back-to-Back* (event does not immediately follow another event, but does immediately precede another event); *Later in Back-to-Back* (another event immediately precedes this event, without a break); and *Cumulative* (number of hours of event that precede this event over the whole day). A 'default' event for which all of these characteristics take the value zero, would be the first of the day, but each student has subsequent events that day after a break.

Figure 3: Overall Attendance Pattern



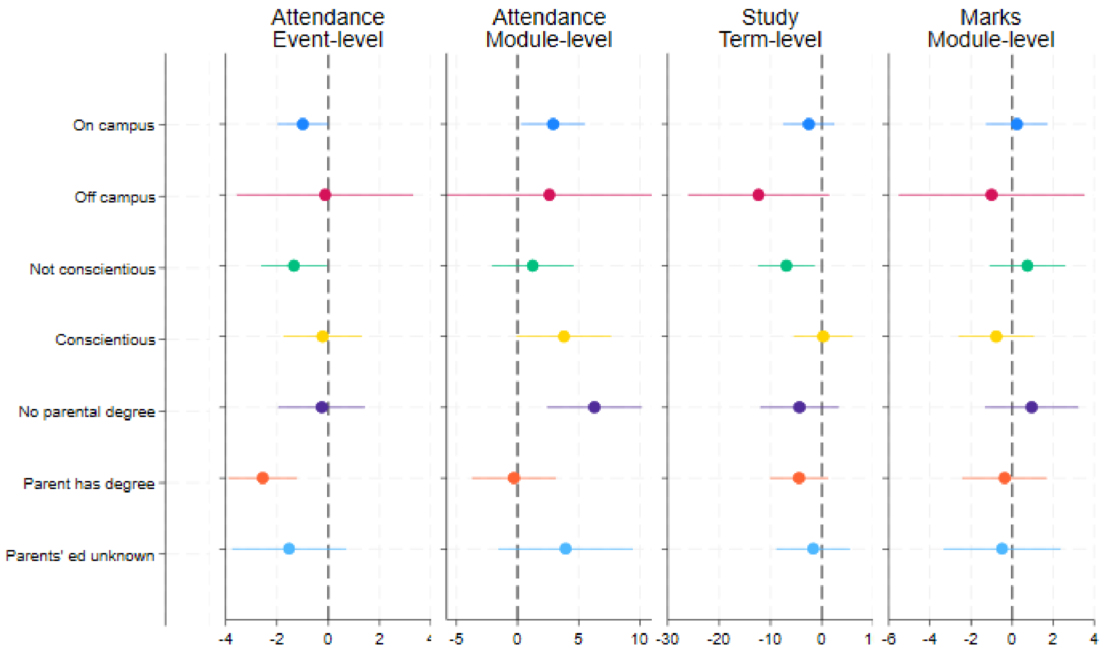
Notes: Top panel plots mean percentage of events attended each week in fall and spring term. Each person weighted equally, and within each person, each event equally. Bottom panel plots proportion of individuals with at least one timetabled event who attend zero events, each week in fall and spring term.

Figure 4: Mean first-year overall marks by decile of overall attendance



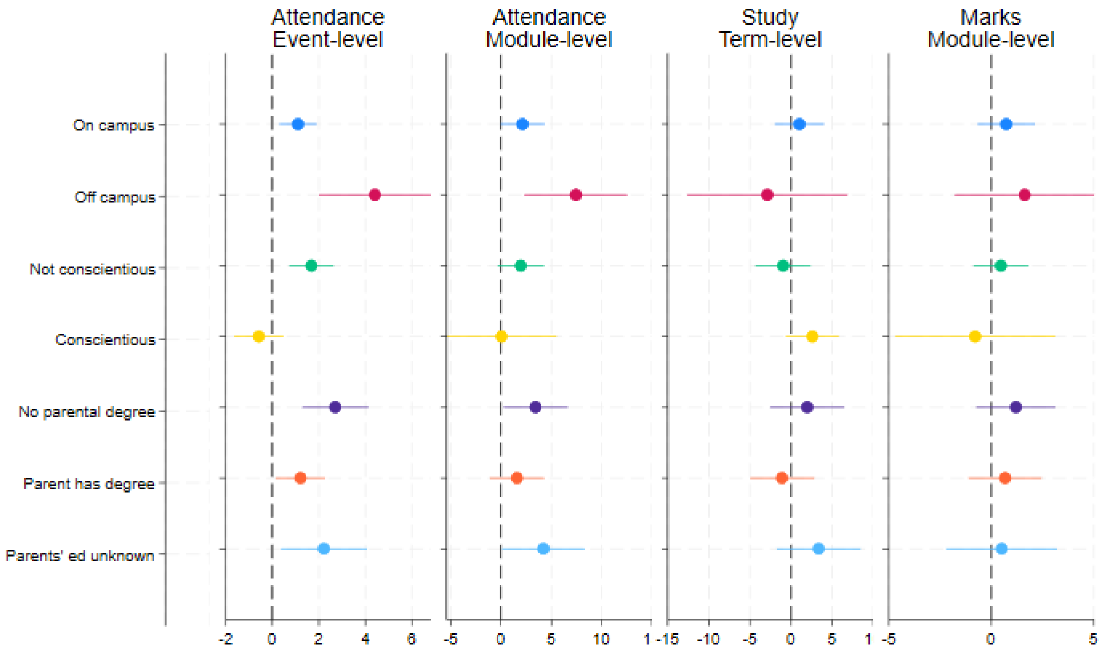
Notes: Unconditional margins, with 95% confidence intervals derived from standard errors clustered by programme, N=1820 first-year students with valid first-year overall mark. Decile upper bounds (%): p1 (sample minimum): 0; p10 (upper bound of decile 1): 37.7, p20: 48.5, p30: 54.8, p40: 61.6, p50: 67.0, p60: 73.4, p70: 78.6, p80: 83.9, p90: 90.2, p100 (sample maximum): 100

Figure 5: Heterogeneity of effect of *Only* events by student characteristics



Notes: Markers show estimated treatment effect, and horizontal lines 90% confidence intervals, for impact of *Only* Event, for the outcome and at the level of aggregation indicated above each graph and for a student with the characteristic shown on the left. For each outcome, estimated from three separate models which interact *Only* and *Back-to-Back* with a student characteristic: By campus residence (base is on-campus, interaction is with off-campus); by conscientiousness (base is not conscientious, interaction term is with conscientious, where conscientious is defined as above the sample median); and by parental higher education (base category is no parental degree; interaction terms are with at least one parent having a degree, and with parental education being unknown).

Figure 6: Heterogeneity of effects of *Back-to-Back* events by student characteristics



Notes: Markers show estimated treatment effect, and horizontal lines 90% confidence intervals, for impact of *Back-to-Back* Event, for the outcome and at the level of aggregation indicated above each graph and for a student with the characteristic shown on the left. For each outcome, estimated from three separate models which interact *Only* and *Back-to-Back* with a student characteristic: By campus residence (base is on-campus, interaction is with off-campus); by conscientiousness (base is not conscientious, interaction term is with conscientious, where conscientious is defined as above the sample median); and by parental higher education (base category is no parental degree; interaction terms are with at least one parent having a degree, and with parental education being unknown).

Table 1: Summary: Population and sample composition

	(1) Population	(2) Enrolled in BOOST	(3) Difference	(4) (p-value)
Female	0.502	0.524	-0.021	(0.164)
Mature (age 21+)	0.095	0.078	0.017	(0.053)
Nationality/SES grouping:				
Home High SES	0.402	0.415	-0.013	(0.385)
Home Low SES	0.272	0.279	-0.007	(0.621)
Home SES Unclassified	0.009	0.005	0.004	(0.130)
EU	0.164	0.159	0.005	(0.630)
International	0.152	0.142	0.010	(0.335)
Parents' education:				
Parent has degree	0.465	0.476	-0.011	(0.474)
Neither parent has degree	0.333	0.337	-0.003	(0.827)
Parents' ed' unknown	0.201	0.187	0.014	(0.245)
Ethnicity:				
White	0.588	0.560	0.029	(0.056)
Asian	0.160	0.165	-0.005	(0.652)
Black	0.159	0.184	-0.024*	(0.033)
Ethnicity unknown/refused	0.009	0.007	0.002	(0.402)
Mixed ethnicity	0.059	0.065	-0.006	(0.374)
Other ethnicity	0.024	0.020	0.005	(0.282)
Entry qualifications:				
A-Levels and Highers	0.559	0.587	-0.028	(0.065)
International Baccalaureate	0.030	0.028	0.002	(0.717)
Other Level 3 or HE Level	0.180	0.145	0.035**	(0.002)
Other Level 2	0.085	0.086	-0.001	(0.922)
Entry quals missing / unknown	0.146	0.154	-0.009	(0.423)
Students' entry tariff score:				
Lowest Quintile	0.145	0.151	-0.006	(0.566)
2nd	0.161	0.168	-0.007	(0.556)
3rd	0.132	0.131	0.001	(0.913)
4th	0.155	0.162	-0.006	(0.575)
Highest Quintile	0.145	0.153	-0.008	(0.461)
Missing	0.261	0.235	0.026*	(0.050)
Field of Study:				
Humanities	0.269	0.271	-0.002	(0.883)
Social Science	0.411	0.413	-0.002	(0.875)
Science and Health	0.320	0.315	0.004	(0.760)
Residence:				
Live on campus	0.841	0.887	-0.046***	(0.000)
Observations	2,621	1,837		

Notes: Summarizes composition of students in first-year cohort (Column 1) vs those enrolled in our study (Column 2). Column 3 shows the difference in means between Columns 1 and 2 and Column 4 has the corresponding t-test's p-value.

Table 2: Summary: timetables and attendance rates

	(1) All mean/sd	(2) Weighted mean/sd	(3) Avg. student-week mean/sd	(4) Avg. student-module mean/sd	(5) Avg. student-term mean/sd
N Events Attended			5.84	19.99	51.51
			(2.21)	(8.14)	(18.33)
N Events Scheduled			8.82	32.90	83.69
			(1.50)	(9.31)	(13.24)
Total duration, minutes			698.38	2612.46	6646.98
			(124.55)	(727.48)	(1126.24)
Only Event	0.14	0.15	1.16	4.43	11.55
	(0.34)	(0.36)	(0.79)	(2.85)	(7.03)
First of Back-to-Back	0.21	0.20	1.83	6.85	17.27
	(0.40)	(0.40)	(0.91)	(3.47)	(7.67)
Later in Back-to-Back	0.27	0.26	2.40	9.11	22.34
	(0.44)	(0.44)	(1.22)	(5.15)	(10.33)
Cumulative Hours	1.12	1.09	9.98	37.08	93.46
	(1.28)	(1.27)	(4.48)	(18.96)	(37.93)
0900	0.15	0.14	1.33	5.10	12.70
	(0.36)	(0.35)	(0.97)	(3.99)	(8.94)
1000	0.14	0.14	1.22	4.82	11.51
	(0.34)	(0.35)	(0.95)	(4.34)	(9.05)
1100	0.15	0.16	1.32	5.17	12.86
	(0.36)	(0.37)	(0.83)	(3.65)	(7.90)
1200	0.09	0.08	0.77	2.88	7.27
	(0.28)	(0.28)	(0.74)	(2.77)	(6.88)
1300	0.10	0.10	0.84	3.28	8.13
	(0.30)	(0.30)	(0.71)	(3.03)	(6.69)
1400	0.10	0.10	0.87	3.08	8.41
	(0.30)	(0.30)	(1.09)	(3.55)	(9.97)
1500	0.11	0.11	1.02	3.48	9.18
	(0.31)	(0.32)	(1.06)	(3.20)	(8.66)
1600	0.09	0.09	0.78	2.84	7.52
	(0.29)	(0.28)	(0.74)	(2.78)	(6.68)
Lecture	0.56	0.55	4.92	18.06	47.13
	(0.50)	(0.50)	(1.82)	(6.93)	(17.45)
Lab	0.08	0.08	0.70	2.38	6.69
	(0.27)	(0.26)	(0.81)	(2.74)	(8.58)
Class / other	0.36	0.37	3.19	12.47	29.87
	(0.48)	(0.48)	(1.69)	(7.90)	(15.77)
Module Size	226.35	216.63			
	(133.97)	(138.59)			
Attendance, %	65.41	65.99			
	(45.03)	(45.23)			
Observations:					
N students	1,837	1,837	1,837	1,837	1,837
N events	11,346	11,346			
N student-events	307,488	307,488			
N student-weeks			36,740		
N student-modules				15,162	
N student-terms					3,592

Notes: Shows summary of primary analysis sample. Column 1 summarizes all student-events, providing equal weight to each. Column 2 weights events so that each student is given equal weight. Column 3 summarizes the timetable load for a student's typical week, based on third week of the autumn/fall and spring terms. Column 4 summarizes the timetable load for an average student-module, giving each student equal weight. Column 5 summarizes the timetable load for an average student-term, giving each student equal weight. Additional timetable controls in primary specification include: day of week dummy variables, relative teaching group size, and event share type.

Table 3: Balance test: Regression of daily structure on student characteristics across levels of aggregation. All students

	(1) Only Event	(2) First of Back-to-Back	(3) Later in Back-to-Back	(4) Cumulative Hours
Panel A: Student-Event level data: Programme + Module Fixed Effects				
Female	-0.003	-0.001	0.002	0.018
	(0.004)	(0.003)	(0.004)	(0.011)
Home Low SES	-0.002	0.006*	0.007	0.014
	(0.004)	(0.004)	(0.005)	(0.012)
Home Unclassified	-0.000	0.014	0.007	-0.011
	(0.017)	(0.018)	(0.017)	(0.033)
EU	-0.004	-0.007	-0.008	-0.010
	(0.008)	(0.006)	(0.008)	(0.022)
International	0.006	0.005	-0.001	0.012
	(0.007)	(0.006)	(0.008)	(0.022)
Mature (age 21+)	-0.000	0.010*	0.011	0.014
	(0.007)	(0.006)	(0.007)	(0.018)
Parents' ed' unknown	0.0019	-0.005	0.011**	0.011
	(0.005)	(0.004)	(0.005)	(0.015)
Parent has degree	-0.006	-0.004	0.003	0.010
	(0.004)	(0.004)	(0.005)	(0.012)
Asian	0.001	-0.004	-0.009	-0.009
	(0.006)	(0.005)	(0.007)	(0.018)
Black	0.005	-0.001	-0.003	0.003
	(0.005)	(0.004)	(0.005)	(0.014)
Ethnicity unknown/refused	-0.008	-0.009	0.015	0.002
	(0.025)	(0.010)	(0.022)	(0.055)
Mixed ethnicity	-0.002	0.000	-0.003	-0.037*
	(0.006)	(0.005)	(0.007)	(0.020)
Other ethnicity	-0.021*	-0.012	-0.018	0.030
	(0.012)	(0.011)	(0.013)	(0.040)
Conscientiousness	-0.001	-0.000	0.003	-0.005
	(0.002)	(0.002)	(0.002)	(0.005)
Discount factor	-0.004	-0.000	-0.004	0.011
	(0.003)	(0.003)	(0.004)	(0.009)
Live off campus	-0.004	0.003	0.030***	0.017
	(0.006)	(0.005)	(0.011)	(0.017)
F	1.037	0.933	1.403	1.260
$p(F)$	0.413	0.555	0.093	0.179
adjusted p	0.797	0.867	0.243	0.427
Observations	307,488	307,488	307,488	307,488
Panel B: Student-Module level data: Programme + Module Fixed Effects				
F	0.947	1.087	1.242	1.041
$p(F)$	0.536	0.350	0.193	0.408
adjusted p	0.897	0.637	0.446	0.774
Observations	15,162	15,162	15,162	15,162
Panel C: Student-term level data: Programme Fixed Effects				
F	0.837	0.925	1.291	0.838
$p(F)$	0.671	0.567	0.157	0.690
adjusted p	0.976	0.838	0.337	0.905
Observations	3,592	3,592	3,592	3,592

Notes: Singleton observations dropped. Standard errors clustered by individual in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. "Lives on campus" is excluded from calculation of F-test for joint significance. Additional individual-level controls included in F-test for joint significance: Entry qualification type (2 dummies); entry qualification total tariff score (5 quintile dummies). Additional module and group controls in event-level specification: Event type, event-type share, and relative size of teaching group. Omitted categories are: male, Home High-SES, young (age <21), neither parent has a university degree, White ethnicity, entry qualifications are A-Level, and entry tariff Q1 (lowest). Adjusted p-values account for testing of multiple hypotheses using the following modified Bonferroni Adjustment: $p_{adj} = 1 - (1 - p(k))^{g(k)}$ $where$ $g(k) = M^{1-r(.k)}$, where M is the number of outcomes being tested (here 4 timetable characteristics), $p(k)$ is the unadjusted p-value for the k^{th} outcome and $r(.k)$ is the mean of the (absolute) pairwise correlations between all the outcomes other than k.(See Sankoh, Huque and Dubey, 1997, pp.2534-2535, for discussion).

Table 4: Balance test: Regression of daily structure on student characteristics across levels of aggregation. Students living on campus only

	(1) Only Event	(2) First of Back-to-Back	(3) Later in Back-to-Back	(4) Cumulative Hours
Panel A: Student-Event level data: Programme + Module Fixed Effects				
Female	-0.001	-0.002	0.001	0.014
	(0.004)	(0.004)	(0.004)	(0.012)
Home Low SES	-0.004	0.006	0.007	0.018
	(0.004)	(0.004)	(0.005)	(0.013)
Home Unclassified	-0.006	0.020	0.016	-0.013
	(0.023)	(0.025)	(0.022)	(0.045)
EU	-0.004	-0.009	-0.011	-0.012
	(0.008)	(0.006)	(0.009)	(0.023)
International	0.003	0.007	0.001	0.025
	(0.007)	(0.006)	(0.008)	(0.022)
Mature (age 21+)	0.006	0.011	0.008	-0.023
	(0.007)	(0.008)	(0.009)	(0.021)
Parents' ed' unknown	0.004	-0.007	0.010	0.014
	(0.005)	(0.005)	(0.006)	(0.016)
Parent has degree	-0.006	-0.006	-0.000	0.006
	(0.004)	(0.004)	(0.005)	(0.013)
Asian	-0.003	-0.008	-0.009	-0.004
	(0.006)	(0.005)	(0.007)	(0.019)
Black	0.002	-0.003	-0.004	0.002
	(0.005)	(0.004)	(0.005)	(0.015)
Ethnicity unknown/refused	0.004	-0.015	0.017	0.028
	(0.029)	(0.011)	(0.025)	(0.060)
Mixed ethnicity	-0.003	-0.003	-0.001	-0.039*
	(0.006)	(0.006)	(0.008)	(0.021)
Other ethnicity	-0.024*	-0.016	-0.021	0.029
	(0.014)	(0.012)	(0.014)	(0.045)
Conscientiousness	-0.000	-0.001	0.002	-0.005
	(0.002)	(0.002)	(0.002)	(0.006)
Discount factor	-0.004	0.001	-0.001	0.010
	(0.003)	(0.003)	(0.004)	(0.0105)
F	0.944	1.062	1.160	1.260
$p(F)$	0.541	0.381	0.269	0.179
adjusted p	0.903	0.694	0.592	0.427
Observations	273,731	273,731	273,731	273,731
Panel B: Student-Module level data: Programme + Module Fixed Effects				
F	0.768	1.231	1.039	1.055
$p(F)$	0.781	0.203	0.410	0.390
adjusted p	0.989	0.414	0.766	0.754
Observations	13,465	13,465	13,465	13,465
Panel C: Student-term level data: Programme Fixed Effects				
F	0.852	0.982	1.156	0.831
$p(F)$	0.670	0.487	0.273	0.699
adjusted p	0.971	0.767	0.537	0.910
Observations	3,184	3,184	3,184	3,184

Notes: Singleton observations dropped. Standard errors clustered by individual in parentheses. ***: $p<0.01$, **: $p<0.05$, *: $p<0.1$. Additional individual-level controls included in F-test for joint significance: Entry qualification type (2 dummies); entry qualification total tariff score (5 quintile dummies). Additional module and group controls in event-level specification: Event type, event-type share, and relative size of teaching group. Omitted categories are: male, Home High-SES, young (age <21), neither parent has a university degree, White ethnicity, entry qualifications are A-Level, and entry tariff Q1 (lowest). Adjusted p-values account for testing of multiple hypotheses using the following modified Bonferroni Adjustment: $p_{adj} = 1-(1-p(k))^{g(k)}\ where\ g(k) = M^{1-r(.k)}$, where M is the number of outcomes being tested (here 4 timetable characteristics), $p(k)$ is the unadjusted p-value for the k^{th} outcome and $r(.k)$ is the mean of the (absolute) pairwise correlations between all the outcomes other than k.(See Sankoh, Huque and Dubey, 1997, pp.2534-2535, for discussion).

Table 5: Balance test: Regression of daily structure on module and event characteristics

	(1) Only Event	(2) First of Back-to-Back	(3) Later in Back-to-Back	(4) Cumulative Hours
Module Size (100s of students)	-0.006	-0.010	0.021	0.008
	(0.011)	(0.014)	(0.016)	(0.058)
Event Type Share	-0.050	0.062	0.047	0.314
	(0.044)	(0.065)	(0.068)	(0.219)
Relative Teaching Group Size	-0.041	-0.036	-0.073	-0.238
	(0.062)	(0.066)	(0.090)	(0.266)
Coursework Weight (1=100%)	-0.047	0.051	0.088	0.225
	(0.072)	(0.100)	(0.113)	(0.413)
Compulsory module	-0.052	0.015	-0.009	0.274*
	(0.036)	(0.045)	(0.053)	(0.161)
Core module	-0.015	0.030	-0.058	0.101
	(0.020)	(0.041)	(0.049)	(0.114)
F	0.984	0.701	1.067	1.047
$p(F)$	0.435	0.649	0.380	0.393
adjusted p	0.819	0.925	0.745	0.756
Observations	307,476	307,476	307,476	307,476

Notes: Standard errors clustered by event in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. Additional controls not included in joint-F test: Duration of teaching event; event type (lecture, lab, etc.), programme fixed-effects. Adjusted-p values calculated as described in Table 3.

Table 6: Effect of timetable characteristics on attendance and performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Attendance, %, Event-level			Attendance, %, Module-level			Mark, /100, Module-level		
	Convenience only	Convenience +day-long fatigue	+ consecutive fatigue	Convenience only	Convenience + day-long fatigue	+ consecutive fatigue	Convenience only	Convenience +day-long fatigue	+ consecutive fatigue
Default = First-in-day, with other events to follow after a break									
Only Event	-0.802*	-0.920*	-0.881*	2.224*	2.815**	2.645**	0.328	0.091	0.140
	(0.466)	(0.482)	(0.485)	(1.276)	(1.323)	(1.344)	(0.734)	(0.761)	(0.777)
Back-to-Back Event	1.394***	1.456***		3.015***	2.705**		0.698	0.823	
	(0.374)	(0.378)		(1.051)	(1.053)		(0.674)	(0.677)	
First of Back-to-Back			1.616***			2.008*			1.023
			(0.406)			(1.214)			(0.756)
Later in Back-to-Back			1.277***			3.397***			0.625
			(0.430)			(1.204)			(0.824)
Cumulative Hours		-0.177	-0.130		1.005**	0.792		-0.404	-0.343
		(0.168)	(0.178)		(0.510)	(0.569)		(0.298)	(0.345)
Start-time: *Omitted = 0900 start*									
1000-1200	5.695***	5.783***	5.805***	9.146***	8.627***	8.541***	0.393	0.602	0.626
	(0.569)	(0.587)	(0.587)	(1.679)	(1.728)	(1.730)	(1.088)	(1.115)	(1.116)
1300-1400	8.459***	8.709***	8.676***	12.58***	11.08***	11.06***	1.199	1.804	1.809
	(0.675)	(0.734)	(0.738)	(2.030)	(2.245)	(2.245)	(1.259)	(1.387)	(1.386)
1500-1800	8.675***	9.057***	9.033***	13.84***	11.95***	12.19***	1.978	2.738*	2.669*
	(0.634)	(0.775)	(0.777)	(1.968)	(2.316)	(2.350)	(1.305)	(1.528)	(1.544)
Day-of-week: *Omitted = Monday*									
Midweek	-2.731***	-2.711***	-2.712***	-4.980***	-4.665***	-4.730***	-1.772**	-1.899**	-1.880**
	(0.418)	(0.421)	(0.421)	(1.391)	(1.382)	(1.386)	(0.894)	(0.892)	(0.895)
Friday	-5.166***	-5.137***	-5.146***	-8.743***	-8.657***	-8.710***	-0.0870	-0.121	-0.106
	(0.491)	(0.493)	(0.493)	(1.546)	(1.547)	(1.553)	(1.032)	(1.034)	(1.036)
Dep var mean	65.40	65.40	65.40	65.32	65.32	65.32	60.31	60.31	60.31
(standard dev')	(45.03)	(45.03)	(45.03)	(24.89)	(24.89)	(24.89)	(14.48)	(14.48)	(14.48)
Observations	289,325	289,325	289,325	14,982	14,982	14,982	14,982	14,982	14,982

Notes: Standard errors clustered by individual in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. All specifications weight each person equally, and within each person each event equally. Additional controls in all columns: Programme plus module fixed effects, dummy variables for individual characteristics shown in Table 1. Event-level specifications in Columns 1, 4, 7 also includes event type dummy variables, event type share, and relative teaching group size. In all module-level columns, all timetable characteristics are the within-person mean across all their events on the module.

Table 7: Effect of timetable characteristics on additional measures of academic performance

	(1) Overall Mark	(2) Overall ≥ 70	(3) Overall ≥ 60	(4) Coursework Mark	(5) Coursework ≥ 70	(6) Coursework ≥ 60
Default = First-in-day, with other events to follow after a break						
Only Event	0.091	-0.031	0.025	0.599	-0.023	-0.003
	(0.761)	(0.024)	(0.028)	(0.836)	(0.026)	(0.027)
Back-to-Back Event	0.823	0.009	0.011	0.718	0.011	0.012
	(0.677)	(0.020)	(0.022)	(0.703)	(0.021)	(0.023)
Cumulative Hours	-0.404	-0.016*	-0.002	-0.280	-0.011	-0.013
	(0.298)	(0.010)	(0.011)	(0.339)	(0.010)	(0.011)
Start-time: *Omitted = 0900 start*						
1000-1200	0.602	-0.002	0.023	0.631	-0.031	0.022
	(1.115)	(0.034)	(0.039)	(1.190)	(0.036)	(0.039)
1300-1400	1.804	0.078*	-0.026	1.372	-0.032	0.047
	(1.387)	(0.042)	(0.051)	(1.507)	(0.044)	(0.049)
1500-1800	2.738*	0.070	0.032	2.598	-0.006	0.057
	(1.528)	(0.046)	(0.051)	(1.665)	(0.047)	(0.052)
Day-of-week: *Omitted = Monday*						
Midweek	-1.899**	-0.062**	-0.090***	-1.994**	-0.040	-0.050
	(0.892)	(0.028)	(0.033)	(0.975)	(0.031)	(0.033)
Friday	-0.121	-0.010	0.024	1.241	0.082**	0.031
	(1.034)	(0.033)	(0.039)	(1.062)	(0.036)	(0.039)
Dep var mean	60.31	0.248	0.574	65.48	0.294	0.609
(standard dev)	(14.48)	(0.432)	(0.495)	(24.85)	(0.456)	(0.487)
Observations	14,982	14,982	14,982	14,762	14,762	14,762

Notes: Standard errors clustered by individual in parentheses. ***: p <0.01, **: p <0.05, *: p <0.1. All specifications weight each person equally, and within each person each event equally. all mark outcomes are at the module-level. Additional controls in all columns: Programme plus module fixed effects, dummy variables for individual characteristics shown in Table 1. Event-level specifications in columns 1 and 4 also includes event type dummy variables, event type share, and relative teaching group size. In all module-level columns, all timetable characteristics are the within-person mean across all their events on the module. Columns 4-6 all restrict to modules with a non-zero coursework weighting.

Table 8: Effect of timetable characteristics on attendance and performance excluding (students with) optional modules

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Dropping optional modules				Dropping students with any optional modules		
	Attendance, % Event-level	Attendance, % Module-level	Overall Mark /100 Module-level	Coursework Mark /100 Module-level	Attendance, % Event-level	Attendance, % Module-level	Overall Mark /100 Module-level	Coursework Mark /100 Module-level
Default = First-in-day, with other events to follow after a break								
Only Event	-0.860	2.985**	0.139	0.027	-0.471	6.131***	1.679	0.608
	(0.548)	(1.476)	(0.876)	(0.938)	(0.610)	(1.931)	(1.290)	(1.360)
Back-to-Back Event	1.317***	3.055***	1.252	1.275*	2.048***	6.719***	2.091*	1.232
	(0.402)	(1.142)	(0.761)	(0.773)	(0.463)	(1.597)	(1.128)	(1.091)
Cumulative Hours	0.086	1.042*	-0.517	-0.468	-0.536***	0.529	-1.110***	-1.017**
	(0.180)	(0.570)	(0.324)	(0.373)	(0.172)	(0.659)	(0.397)	(0.460)
Start-time: *Omitted = 0900 start*								
1000-1200	6.326***	8.172***	0.216	0.512	5.647***	4.169*	0.311	0.228
	(0.678)	(1.913)	(1.271)	(1.323)	(0.824)	(2.332)	(1.522)	(1.570)
1300-1400	10.072***	10.451***	1.100	0.855	9.299***	7.346**	1.500	1.242
	(0.829)	(2.463)	(1.517)	(1.642)	(0.970)	(3.324)	(2.206)	(2.348)
1500-1800	10.742***	11.749***	2.838	2.989	11.154***	11.723***	3.795*	3.467
	(0.885)	(2.589)	(1.724)	(1.830)	(1.044)	(3.112)	(2.101)	(2.255)
Day-of-week: *Omitted = Monday*								
Midweek	-2.499***	-4.747***	-2.634***	-2.411**	-3.575***	-5.502***	-3.229**	-3.410**
	(0.486)	(1.506)	(0.943)	(1.049)	(0.496)	(1.887)	(1.265)	(1.353)
Friday	-4.698***	-8.327***	-0.777	0.757	-6.307***	-8.348***	-0.079	0.409
	(0.552)	(1.701)	(1.146)	(1.185)	(0.577)	(1.898)	(1.335)	(1.341)
Dep var mean	66.70	65.73	60.79	62.02	66.57	65.26	59.39	62.66
(standard dev)	(44.83)	(24.64)	(14.63)	(15.91)	(44.43)	(24.82)	(15.34)	(16.77)
Observations	246,081	12,568	12,568	12,568	165,614	8,576	8,576	8,576

Notes: Standard errors clustered by individual in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. All specifications weight each person equally, and within each person each event equally. Additional controls in all columns: Programme plus module fixed effects, dummy variables for individual characteristics shown in Table 1. Event-level specifications in Columns 1 and 5 also includes event type dummy variables, event type share, and relative teaching group size. In all module-level columns, all timetable characteristics are the within-person mean across all their events on the module. For sample consistency all columns restrict to modules with non-zero coursework weighting

Table 9: Effect of timetable characteristics on term-level attendance, study habits and competing time uses

	(1) Attendance, %	(2) Study hours per week	(3) Cramming - often or always	(4) Work for pay
Default = First-in-day, with other events to follow after a break				
Only Event	3.576	-3.762	0.104	-0.0535
	(3.975)	(2.523)	(0.113)	(0.0868)
Back-to-Back Event	6.874***	0.732	0.0119	0.0467
	(2.658)	(1.550)	(0.0785)	(0.0582)
Cumulative Hours	-1.953	-0.921	-0.0274	0.0221
	(1.813)	(0.887)	(0.0532)	(0.0387)
Start-time: *Omitted = 0900 start*				
1000-1200	1.075	-3.858	0.180	-0.284***
	(4.925)	(2.544)	(0.135)	(0.107)
1300-1400	-1.094	-6.157*	0.234	-0.239*
	(5.958)	(3.357)	(0.162)	(0.124)
1500-1800	6.489	-5.693*	0.0286	-0.299**
	(6.067)	(2.930)	(0.164)	(0.123)
Dayof-week: *Omitted = Monday*				
Midweek	-9.262***	-0.990	0.105	-0.099
	(3.493)	(1.788)	(0.102)	(0.0737)
Friday	-13.909**	-4.868*	0.0720	0.107
	(5.553)	(2.953)	(0.152)	(0.113)
Dependent variable mean	65.56	11.76	0.411	0.196
(std.dev if continuous)	(21.66)	(10.44)		
Observations	3,654	2,365	2,365	2,365

Notes: Standard errors clustered by individual in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. Observations for each wave/term are weighted to profile of BOOST2018 participants. Additional controls in all columns: Programme fixed effects, dummy variables for individual characteristics shown in Table 1, term/wave. All timetable characteristics are the within-person mean across all their events on the term. The outcome variable in Columns 2-4 is equal to one if the student "often" or "always" has this habit. Outcome in Column 4 is binary.

Table 10: Effect of timetable characteristics excluding International students

	(1) Attendance, % Event-level	(2) Attendance, % Module-level	(3) Study hours per week Term-level	(4) Mark /100 Module-level
Default = First-in-day, with other events to follow after a break				
Only Event	-1.199**	2.352	-5.367*	-0.282
	(0.527)	(1.459)	(2.774)	(0.824)
Back-to-Back Event	1.345***	2.227**	0.534	0.374
	(0.407)	(1.128)	(1.631)	(0.704)
Cumulative Hours	-0.136	1.083*	-0.898	-0.325
	(0.180)	(0.580)	(0.958)	(0.319)
Start-time: *Omitted = 0900 start*				
1000-1200	5.231***	8.343***	-2.670	0.931
	(0.638)	(1.899)	(2.639)	(1.177)
1300-1400	8.284***	11.502***	-6.447*	2.317
	(0.787)	(2.419)	(3.591)	(1.480)
1500-1800	8.026***	10.291***	-7.219**	2.879*
	(0.830)	(2.548)	(3.008)	(1.635)
Day-of-week: *Omitted = Monday*				
Midweek	-2.565***	-5.173***	-1.879	-2.391**
	(0.451)	(1.511)	(1.974)	(0.971)
Friday	-4.911***	-8.807***	-6.040**	-0.755
	(0.540)	(1.772)	(3.059)	(1.165)
Dep var mean	64.99	63.62	11.53	60.70
(standard dev)	(45.28)	(25.14)	(10.46)	(14.31)
Observations	248,546	12,823	2,074	12,823

Notes: Standard errors clustered by individual in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. All specifications weight each person equally, and within each person each event equally. Additional controls in all columns: *Cumulative Hours*, programme plus module (or term) fixed effects, dummy variables for individual characteristics shown in Table 1. Column 1 also includes event type dummy variables, event type share, and relative teaching group size. In Columns 2, 3 and 4, all timetable characteristics are the within-person mean across all their events on the module (or term).

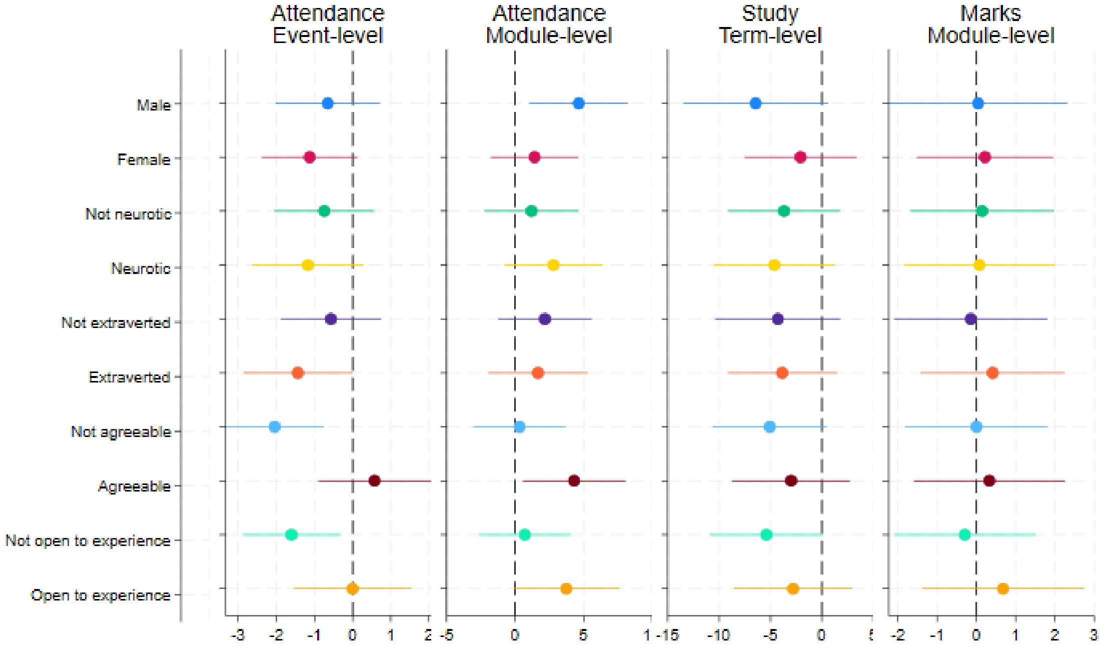
Table 11: Heterogeneity by event type

	(1) Attendance, %, Event-level	(2) Attendance, %, Module-level	(3) Study hours per week, Term-level	(4) Mark /100 Module-level
Only Event	-1.317**	2.578	-9.617*	-0.652
	(0.627)	(2.954)	(5.560)	(1.748)
Only Event × Lab	0.793	12.640	19.102	5.815
	(1.719)	(11.478)	(31.588)	(7.861)
Only Event × Other group teaching	0.100	-0.079	8.951	1.148
	(1.000)	(4.729)	(9.194)	(2.703)
Back-to-Back Event	2.463***	5.359**	2.890	1.014
	(0.427)	(2.337)	(3.977)	(1.437)
Back-to-Back Event × Lab	-4.966***	-21.670**	-7.984	-6.438
	(1.240)	(10.229)	(17.957)	(6.424)
Back-to-Back Event × Other group teaching	-1.636**	-4.422	-4.009	-0.075
	(0.765)	(4.099)	(7.437)	(2.316)
Dependent variable means (std.dev)				
Lectures	70.74			
	(41.69)			
Labs	62.08			
	(48.24)			
Other group teaching	57.57			
	(48.15)			
Observations	289,325	14,982	2,365	14,982

Notes: Standard errors clustered by individual in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. All specifications weight each person equally, and within each person each event equally. Additional controls in all columns: *Cumulative Hours*, programme plus module (or term) fixed effects, dummy variables for individual characteristics shown in Table 1. Column 1 also includes event type dummy variables, event type share, and relative teaching group size. In Columns 2, 3 and 4, all timetable characteristics are the within-person mean across all their events on the module (or term). In this specification event types are split between Lectures (omitted category), Labs, and all others.

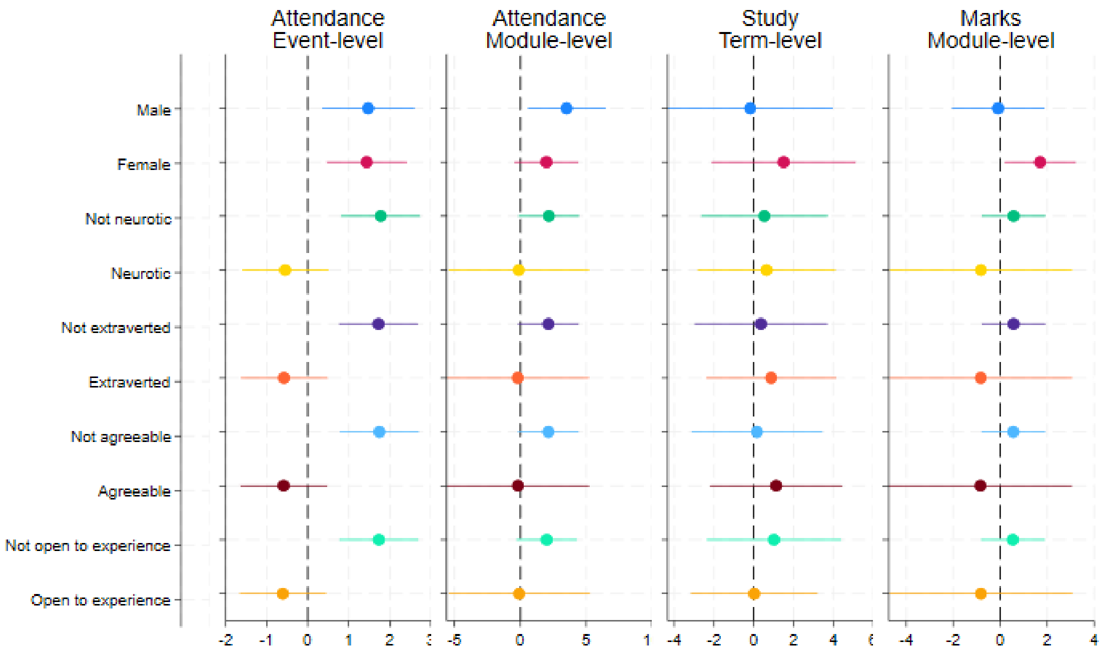
A Appendix

Figure A1: Heterogeneity of effects of *Only* events by additional student characteristics



Notes: Markers show estimated treatment effect, and horizontal lines 90% confidence intervals, for impact of *Only* Event, for the outcome and at the level of aggregation indicated above each graph and for a student with the characteristic shown on the left. For each outcome, estimated from five separate models which interact *Only* and *Back-to-Back* with a student characteristic: By gender (base is male, interaction term is female); and one each for four of the Big 5 personality traits, where the base category is not having the trait (defined as below-median) and the interaction term is with having the trait (above median).

Figure A2: Heterogeneity of effects of *Back-to-Back* events by additional student characteristics



Notes: Markers show estimated treatment effect, and horizontal lines 90% confidence intervals, for impact of *Back-to-Back* Event, for the outcome and at the level of aggregation indicated above each graph and for a student with the characteristic shown on the left. For each outcome, estimated from five separate models which interact *Only* and *Back-to-Back* with a student characteristic: By gender (base is male, interaction term is female); and one each for four of the Big 5 personality traits, where the base category is not having the trait (defined as below-median) and the interaction term is with having the trait (above median).

Table A1: Sensitivity to alternative clustering of standard errors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Main estimation sample			Dropping optional modules			Dropping students with any optional modules		
	Attendance, %	Attendance, %	Mark, /100	Attendance, %	Attendance, %	Mark, /100	Attendance, %	Attendance, %	Mark, /100
Clustering:	Event-level *Student × Weekly event*	Module-level *Student × Module*	Module-level *Student × Module*	Event-level *Student × Weekly event*	Module-level *Student × Module*	Module-level *Student × Module*	Event-level *Student × Weekly event*	Module-level *Student × Module*	Module-level *Student × Module*
Default = First-in-day, with other events to follow after a break									
Only Event	-0.920	2.815*	0.091	-1.211*	3.142*	0.528	-0.471	6.131***	1.679
	(0.613)	(1.439)	(0.750)	(0.682)	(1.665)	(0.930)	(0.856)	(2.087)	(1.346)
Back-to-Back Event	1.456***	2.705**	0.823	1.294**	3.253**	1.451*	2.048***	6.719***	2.091**
	(0.546)	(1.153)	(0.681)	(0.574)	(1.316)	(0.803)	(0.716)	(1.377)	(1.031)
Cumulative Hours	-0.177	1.005	-0.404	-0.076	1.082	-0.506	-0.536**	0.529	-1.110**
	(0.230)	(0.615)	(0.317)	(0.231)	(0.667)	(0.330)	(0.248)	(0.920)	(0.432)
Start-time: *Omitted = 0900 start*									
1000-1200	5.783***	8.627***	0.602	6.058***	7.714***	0.192	5.647***	4.169	0.311
	(1.004)	(2.116)	(0.962)	(1.102)	(2.322)	(1.066)	(1.377)	(2.584)	(1.303)
1300-1400	8.709***	11.078***	1.804	9.662***	9.875***	0.965	9.299***	7.346*	1.500
	(1.161)	(2.617)	(1.420)	(1.267)	(2.941)	(1.539)	(1.534)	(3.741)	(2.232)
1500-1800	9.057***	11.955***	2.738**	10.572***	11.619***	2.698*	11.154***	11.723***	3.795**
	(1.293)	(2.506)	(1.381)	(1.344)	(2.733)	(1.484)	(1.604)	(3.177)	(1.845)
Day-of-week: *Omitted = Monday*									
Midweek	-2.711***	-4.665***	-1.899**	-2.707***	-4.497**	-2.367***	-3.575***	-5.502**	-3.229***
	(0.649)	(1.711)	(0.790)	(0.702)	(1.940)	(0.871)	(0.801)	(2.658)	(1.150)
Friday	-5.137***	-8.657***	-0.121	-5.040***	-8.570***	-0.406	-6.307***	-8.348***	-0.079
	(0.791)	(2.038)	(0.860)	(0.831)	(2.276)	(0.957)	(0.940)	(3.025)	(1.279)
Observations	289,325	14,982	14,982	246,081	12,568	12,568	165,614	8,576	8,576

Notes: Standard errors in parentheses. Columns 1, 4, 7 clustered at student by weekly-event level; Columns 2-3, 5-6, and 8-9 clustered at student by module level. ***: $p<0.01$, **: $p<0.05$, *: $p<0.1$. All specifications weight each person equally, and within each person each event equally. Additional controls in all columns: programme plus module fixed effects, dummy variables for individual characteristics shown in Table 1. Columns 1, 4, 7 also includes event type dummy variables, event type share, and relative teaching group size. In Columns 2-3, 5-6, and 8-9, all timetable characteristics are the within-person mean across all their events on the module.

Sensitivity to selective measurement error in attendance tracking

A potential concern is that attendance may be mismeasured if students asks a peer to swipe their card. This behaviour is plausibly more common for events that are less convenient (e.g., single-class days or tightly packed schedules), which could generate non-classical and selectively correlated measurement error. If so, our estimated effects of timetable characteristics on attendance could be biased in unknown directions.

Because the implications of such one-sided and selectively correlated measurement error are theoretically ambiguous(Millimet & Parmeter, 2022), we assess its potential impact through simulation. We run three sets of simulations in which we set 'true' attendance for a subset of students and events to zero, assuming that recorded attendance is false. In all, we assume that 10% of students ever undertake the practice of giving their card to a friend to swipe, or swiping then leaving their event. In the first model we assume that they do this in 10% of all events they are recorded in attending. In the second and third we assume that they false-swipe in 20% of *Only* or 20% of *Back-to-Back* events respectively, and 10% of all other events. We undertake 500 replications, randomly drawing a different 10% of students and appropriate percentage of events in each case. The first specification in Table A2 shows that any bias is minimal if the practice of buddy-swiping is uniformly distributed across all events. Unsurprisingly, the second and third specifications show that if this practice is heavily selective, the simulated 'true' coefficients for the relevant timetable characteristic become more negative or less positive . However, this does show that our main conclusions are robust to even this very selective case where the practice is twice as prevalent for the specific types of event we study: Our preferred event-level coefficient on *Only* events may be biased towards zero but was still negative and statistically significant, and the sign switches when moving from event- to module-level data. Our preferred event-level coefficients on *Back-to-Back* events may be positively biased away from zero, but all simulations still yield positive signs.

Table A2: Simulations for sensitivity of findings to selective measurement error in attendance tracking

	Event-level			Module-level		
	Only	Back-to-Back	Cumulative	Only	Back-to-Back	Cumulative
Main spec' coefficient'	-0.920	1.456	-0.177	2.815	2.705	1.005
Simulation with 10% of students buddy-swiping.						
At 10% of all events they are recorded attending						
Mean coefficient	-0.920	1.426	-0.179	2.782	2.695	0.978
(90% CI)	(-1.033, -0.811)	(1.361, 1.508)	(-0.217, -0.143)	(2.457, 3.096)	(2.476, 2.923)	(0.870, 1.091)
At 20% of *Only* events, 10% of all other events						
Mean coefficient	-1.592	1.423	-0.174	2.088	2.693	0.976
(90% CI)	(-1.776, -1.433)	(1.337, 1.506)	(-0.216, -0.133)	(1.709, 2.501)	(2.448, 2.929)	(0.849, 1.100)
At 20% of *Back-to-Back* events, 10% of all other events						
Mean coefficient	-0.930	0.728	-0.185	2.750	2.013	0.965
(90% CI)	(-1.049, -0.814)	(0.578, 0.864)	(-0.234, -0.135)	(2.399, 3.098)	(1.679, 2.351)	(0.814, 1.109)

Notes: All from 500 replications of main model reported in columns 2 and 5 of Table 6. 90% confidence interval shows 5th and 95th percentile coefficients across the 500 simulations

Table A3: Associations of attendance, study and marks with the Big 5 personality traits

	(1) Attendance, %, event-level	(2) Attendance, %, module-level	(3) Study hours per week, term-level	(4) Mark /100 module-level
Only Event	-1.834***	1.514	-4.037	-0.022
	(0.510)	(1.408)	(2.487)	(0.780)
Back-to-Back Event	1.510***	1.644	0.610	0.309
	(0.403)	(1.111)	(1.572)	(0.706)
Cumulative Hours	-0.324*	0.639	-1.173	-0.361
	(0.179)	(0.554)	(0.909)	(0.330)
Conscientiousness	4.363***	4.247***	2.131***	2.006***
	(0.592)	(0.612)	(0.272)	(0.343)
Neuroticism	1.140***	1.194***	0.140	0.296
	(0.368)	(0.384)	(0.205)	(0.223)
Extraversion	-1.786***	-1.707***	-0.241	-0.583**
	(0.375)	(0.404)	(0.206)	(0.240)
Agreeableness	0.575	0.550	-0.060	0.129
	(0.463)	(0.486)	(0.277)	(0.280)
Openness	-1.330***	-1.543***	-0.334	-0.247
	(0.488)	(0.503)	(0.322)	(0.293)
Bonferroni-adjusted p-values for significance of the Big 5				
Conscientiousness	0.000	0.000	0.000	0.000
Neuroticism	0.010	0.010	1.000	0.926
Extraversion	0.000	0.000	1.000	0.076
Agreeableness	1.000	1.000	1.000	1.000
Openness	0.033	0.011	1.000	1.000
Observations	231,189	11,934	2,281	11,934

Notes: Standard errors clustered by individual in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. All specifications weight each person equally, and within each person each event equally. Additional controls in all columns: *Cumulative Hours*, programme plus module (or term) fixed effects, dummy variables for individual characteristics shown in Table 1. Column 1 also includes event type dummy variables, event type share, and relative teaching group size. In Columns 2, 3 and 4, all timetable characteristics are the within-person mean across all their events on the module (or term).